

Article

Evaluation of Technical Readiness of the Whole-Process Optimized Fertilization Plan for *Vitis vinifera* ‘Red Globe’ at a County Scale

Cheng Xie ^{1,2,†}, Rong Ma ^{3,†}, Haining Wang ^{1,†}, Chilin Bianma ¹, Ting Li ¹, Zhijiang Chang ^{1,2}, Yuyun Wang ^{1,2,*} and Zhi Xu ^{1,2,*} 

¹ International Joint Laboratory for Resource Utilization of Agricultural Solid Waste in Yunnan Province, College of Resources and Environmental Science, Yunnan Agricultural University, Kunming 650201, China; xiecheng1214@163.com (C.X.); hnwang636@163.com (H.W.); 13378875282@163.com (C.B.); 18003975565@163.com (T.L.); 17615459245@163.com (Z.C.)

² Key Laboratory for Improving Quality and Productivity of Arable Land of Yunnan Province, College of Resources and Environmental Science, Yunnan Agricultural University, Kunming 650201, China

³ College of Economics and Management, Yunnan Agricultural University, Kunming 650201, China; 2011019@ynau.edu.cn

* Correspondence: yuyunwhere@163.com (Y.W.); xuzhi9910@126.com (Z.X.)

† These authors contributed equally to this work.

Abstract

Excessive fertilization in grape production reduces profitability and harms the environment. A five-year field experiment and household survey in Xiangyun County, Yunnan, evaluated a whole-process optimized fertilization plan for *Vitis vinifera* ‘Red Globe’ (hereafter abbreviated as Red Globe Grapes) and its spatial diffusion. The optimized plan reduced N, P₂O₅, and K₂O inputs by 385.28, 298.65, and 154.02 kg ha^{−1}, increased yield by 18.4%, and raised net income by 41,574 RMB ha^{−1}. After five years, partial factor productivity of nitrogen (PFPN, an indicator of nutrient management performance used here to assess adoption at the farmer level)—a proxy for technical readiness—was highest in the core demonstration area and declined with distance. Spatial Durbin modeling showed that spillover effects attenuated beyond roughly 30 km, with an optimal promotion radius near 10 km and an effective promotion radius of 17.5 km. Farmer education generated positive indirect spillovers. Promotion intensity had a negative local effect but net positive spatial feedback. In the development area, adoption remained unstable without sustained support. Scaling optimized fertilization therefore requires differentiated extension strategies that leverage social learning among neighboring farmers.

Keywords: *Vitis vinifera* ‘Red Globe’; optimized fertilization; reducing costs and increasing income; partial factor productivity of nitrogen (PFPN); technical readiness; Spatial Durbin Model



Academic Editor: Spyridon A. Petropoulos

Received: 12 August 2026

Revised: 24 September 2026

Accepted: 5 October 2026

Published: 8 October 2026

Copyright: © 2026 by the authors.

Licensee MDPI, Basel, Switzerland.

This article is an open access article distributed under the terms and conditions of the [Creative Commons Attribution \(CC BY\)](https://creativecommons.org/licenses/by/4.0/) license.

1. Introduction

Grapes are cultivated worldwide, and China ranks among the major producers, with recent expansions in both area and technology [1]. Red Globe Grapes is one of the most widely planted table grape cultivars in China [2]. In Yunnan Province, the subtropical plateau monsoon climate enables off-season production, making it a key region for early- and late-maturing grapes, where Red Globe Grapes is the dominant variety [3,4]. It is a late-maturing, seeded cultivar with very large berries, thick skin, and firm flesh; these traits give

it good storage and transport tolerance. Because these quality traits depend on sustained nutrient supply across a long growing season [5], the Red Globe Grapes cultivar is a suitable system for evaluating optimized fertilization under farmer conditions. Despite expanding cultivation, average yields remain roughly half of the attainable potential [6]. To close this gap, farmers often apply excessive and unbalanced fertilizers [7]. This practice, however, does not proportionally increase yield; instead, it accelerates soil acidification, secondary salinization, and water eutrophication [8–10]. Thus, reconciling productivity, profitability, and environmental sustainability is a pressing challenge for the region's grape industry.

Optimized fertilization—tailoring nutrient supply to crop phenological demand—has improved yields and reduced environmental footprints in various cropping systems [11–16]. For grapes, precision nutrient management can enhance berry quality and economic returns [17–19]. Nevertheless, successful adoption by smallholders remains difficult [9,20,21]. Socioeconomic constraints, cognitive biases, and extension service effectiveness all influence uptake. Participatory approaches, such as farmer field schools, have been promoted to raise awareness [22], but their success depends on local contexts and sustained engagement.

A key unresolved issue is the spatial dynamics of technology diffusion. The Technology Readiness Level (TRL) framework assesses technical maturity [23], yet it often neglects human and spatial factors that determine real-world adoption [24], leading to uneven outcomes even at similar readiness levels [25]. This study uses partial factor productivity of nitrogen (PFPN) as a farmer-level proxy for technical readiness, capturing both the technology's potential and its use under field conditions.

Spatial heterogeneity is fundamental to agricultural innovation diffusion. Tobler's First Law states that near things are more related than distant ones [26,27]. The Spatial Durbin Model (SDM) can quantify direct effects and spatial spillovers of factors such as education, acceptance and promotion intensity [28]. Understanding the distance decay of these effects is critical for efficient extension design [27]. A persistent debate centers on whether adoption is driven more by formal promotion or by social learning among neighbors; evidence suggests both operate but with different spatial signatures.

This study therefore evaluates a whole-process optimized fertilization plan for Red Globe Grapes through a five-year field experiment and farmer survey across three regional typologies (core, coverage, and development zones). This study assesses (i) agronomic and economic performance; (ii) technical readiness (PFPN) achieved after five years of promotion; and (iii) spatial spillover effects and attenuation boundaries using SDM. The novelty of this work lies in linking field-level agronomic and economic outcomes with county-scale spatial diffusion. It uses relative PFPN as an outcome-based farmer-level indicator of nutrient management performance and applies SDM to separate direct and spillover effects of farmer acceptance, education, and promotion intensity. This design allows the study to examine whether field performance translates into spatial adoption and where extension effects attenuate.

2. Materials and Methods

2.1. Study Site

The study was conducted in Xiangyun County, Dali Prefecture, Yunnan Province, China (100°44'5" E, 25°41'6" N). The county covers 2425 km², with eight towns and two townships, and approximately 500,000 residents. The site lies at 1980 m elevation and has a northern subtropical plateau monsoon climate, with a mean annual temperature of 14.7 °C (8.1 °C in January, 19.7 °C in July), mean annual rainfall of 810.8 mm, and annual sunshine duration of 2030–2624 h.

The field experiment was established at Chaoyang, Sanjia Village, Midian Town, on red soil with a gentle slope (~10°). Before the experiment, the topsoil (0–20 cm) had a pH of

6.2, organic matter of 18.4 g kg⁻¹, total N of 1.2 g kg⁻¹, available P of 28.6 mg kg⁻¹, and available K of 156 mg kg⁻¹. Vines were planted in 2013 in an east–west orientation using a single-fence trellis system. Row spacing was 1.5 m and within-row spacing was 0.5 m, with two plants per cluster. The theoretical density was 13,333 plants/ha⁻¹ (8533 plants in the 0.64 ha plot). However, due to the local topography, the actual number of established vines was 8000 on 0.64 ha. First fruiting occurred in 2015; average yield in the first two years was 28,050 kg ha⁻¹, with a sugar content of 11.5%.

2.2. Sampling and Survey Design

Four towns with substantial Red Globe Grapes cultivation were selected: Yunnanyi (YNY), Xiangcheng (XC), Hedian (HD), and Midian (MD). Within these, eight representative villages were chosen to cover the range of vineyard area, farm size, and yield. Sanjia Village (Midian Town) served as the demonstration site for the optimized fertilization technology.

The surrounding villages were classified into three zones based on distance from the demonstration site and the frequency of extension contact: (i) core area—the demonstration village itself, receiving biweekly technical visits and formal training sessions; (ii) coverage area—villages within 10–20 km, receiving monthly extension visits and with access to demonstration plots; and (iii) development area—villages beyond 20 km, receiving only annual mass-media information (leaflets, broadcasts) and occasional farmer-to-farmer contact.

In 2016, face-to-face questionnaire surveys were conducted with 40 randomly selected farmers across the eight villages, covering 27.36 ha of vineyards. The questionnaire captured (a) farmer demographics (age, years of formal education); (b) vineyard management (area, planting density, fertilization frequency, types and amounts of fertilizers, and application method); and (c) economic data (grape selling price, pesticide costs, hired labor costs, and other operating costs). Yield data were obtained from farmers' harvest records for the previous three years and verified against local purchasing station receipts. Net income was calculated as total revenue (yield × price) minus total operating costs (fertilizers, pesticides, machinery, and hired labor).

2.3. Fertilizer Experiment Design

A randomized complete block design was established with four replicates and three treatments: (I) no fertilization (CK); (II) conventional farmer practice (conventional); and (III) whole-process optimized fertilization (improved). Each plot measured 132 m² (four rows × 45 plants per row, 180 plants total).

The conventional treatment followed the average fertilization rates and timings reported by the 40 surveyed farmers in the pre-survey year (2015): total N 832.6 kg ha⁻¹, P₂O₅ 695.9 kg ha⁻¹, and K₂O 873.4 kg ha⁻¹, applied as compound fertilizer (15-15-15) plus urea and potassium sulphate, split over 15 topdressings.

The optimized treatment was designed based on the grape's phenological nutrient demand. Total rates were N 447.3 kg ha⁻¹, P₂O₅ 397.2 kg ha⁻¹, and K₂O 719.4 kg ha⁻¹, applied using conventional compound fertilizers, supplemented with calcium ammonium nitrate (27% N) and magnesium sulphate (16% MgO) to balance Ca and Mg supply. The N:P₂O₅:K₂O ratio was 1:0.89:1.47.

Base fertilizer was applied once before budbreak to all treatments. Soil topdressing was applied 17 times during the growing season: four applications from budbreak to pre-bloom, six from fruit set to pre-veraison, and seven from veraison to pre-harvest. In addition, one foliar spray of boron and zinc was applied at bloom. Thus, the improved treatment received 18 growing-season applications in total (17 soil topdressings + 1 foliar spray), plus the pre-budbreak base fertilizer (Appendix A, Tables A1 and A2). All soil

fertilizers were broadcast in a 50 cm band along the row and incorporated lightly into the soil.

2.4. Promotion Strategy

The optimized technology was promoted continuously from 2016 to 2020 using on-farm demonstrations, one-on-one farmer consultations, group training sessions, instructional videos, online live streams, and printed technical bulletins (Appendix A, Figure A1). In the core area, six formal training sessions were held per year, and individual follow-up visits were conducted every two weeks during the growing season. In the coverage area, four village-level meetings were held per year, and one demonstration plot was maintained per village. In the development area, printed materials were distributed once per year, and one group meeting was conducted per year. The promotion intensity was quantified as the total number of direct extension contacts (training sessions, farm visits, or group meetings attended) per farmer, per year.

2.5. Technical Readiness Assessment

The partial factor productivity of nitrogen (PFPN) was used as a farmer-level indicator of technical readiness:

$$PFPN = \frac{\text{Grape yield (kg/ha)}}{\text{Total N applied (kg/ha)}} \quad (1)$$

The average PFPN of farmers in the core area was set as the benchmark (100%), and relative PFPN for the coverage and development areas was calculated as

$$\text{technical readiness} = \text{Relative PFPN} = \frac{PFPN_z}{PFPN_{core}} \times 100\% \quad (2)$$

where z denotes the coverage or development zone. Higher relative PFPN indicates closer alignment with optimized nutrient management.

2.6. Spatial Durbin Model Specification

To quantify spatial spillover effects, a Spatial Durbin Model (SDM) was estimated:

$$y = \rho Wy + X\beta + WX\theta + \varepsilon \quad (3)$$

where y is the observed outcome (PFPN); X is a matrix of explanatory variables (years of formal education, technology acceptance score, and promotion intensity); W is a row-standardized inverse-distance spatial weight matrix based on Euclidean distances between village centroids; ρ is the spatial autoregressive coefficient; β and θ are coefficients for direct and spatial-lag effects, respectively; and $\varepsilon \sim N(0, \sigma^2 I)$.

The SDM was estimated at the farmer level using 60 farmers' observations. The eight villages were used only to define the spatial reference structure: W was constructed from distances between village centroids, and each farmer was assigned the centroid coordinates of their own village. Therefore, it is possible that farmers in the same village share the same spatial weights. The effective spatial variation is thus at the village level (eight locations), while the estimation unit remains the individual farmer ($n = 60$).

The partial-derivative impact matrix for each explanatory variable:

$$(I - \rho W) - 1(I\beta + W\theta)(I - \rho W) - 1(I\beta + W\theta) \quad (4)$$

Direct effects are the average diagonal elements of this matrix. Indirect effects are the average off-diagonal elements. Total effects are the sum of direct and indirect effects.

2.7. Statistical Analysis

The field experiment data were analyzed using one-way analysis of variance (ANOVA), with treatment means compared by Fisher's least significant difference test at $\alpha = 0.05$. Simple linear regression (ordinary least squares) was used to examine the relationships between total nutrient input and grape yield, and between total nutrient input and the previous year's grape price. Total nutrient input was the predictor; yield or price was the response. R^2 and p -values were obtained from these regressions. Cost-benefit analysis compared total revenue, operating costs, and net income across treatments. Principal component analysis (PCA) was conducted on three farmer-level variables (farmer acceptance, promotion intensity, education level). The components with eigenvalues > 1 were retained, which explained 86.2% of total variance. All statistical analyses were performed in Origin Pro 2026, R version 4.5.1 and IBM SPSS Statistics 21. Statistical significance was set at $p \leq 0.05$ for all tests unless otherwise stated.

3. Results

3.1. Farmer Fertilization Practices and Yield Relationships

Total nutrient input across the 40 surveyed farmers ranged from 819 to 3673 kg ha⁻¹ (CV = 39.4%). Grape yield ranged from 30,000 to 60,000 kg ha⁻¹ (mean = 41,914 kg ha⁻¹). Yield was not significantly associated with total nutrient input in simple linear regression ($R^2 = 0.0058$, $p > 0.05$). In contrast, total nutrient input was positively associated with the previous year's grape price ($R^2 = 0.7702$, $p < 0.01$; Figure 1).

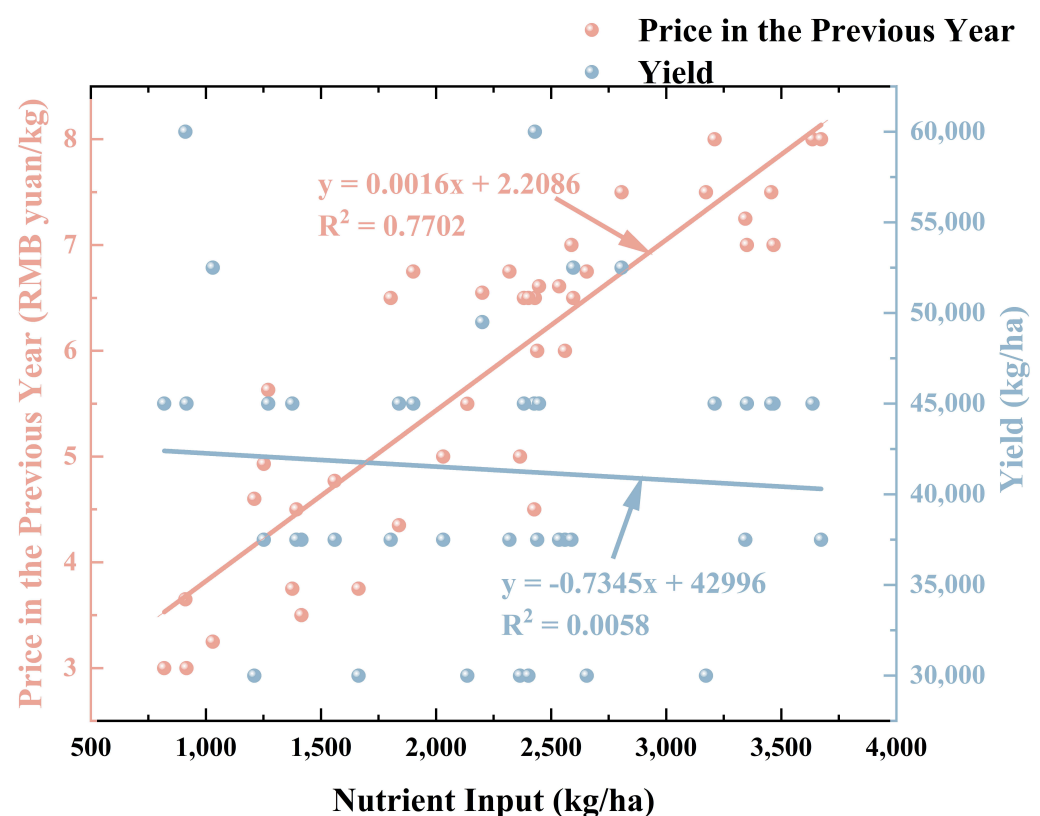


Figure 1. Simple linear regression (ordinary least squares) of grape yield and previous-year grape price on total nutrient input ($n = 40$). The relationship between yield and nutrient input is represented by red data points and a red trend line. The relationship between price and nutrient input is represented by blue data points and a blue trend line.

3.2. Agronomic and Economic Performance of Optimized Fertilization

Relative to the conventional treatment, the optimized treatment increased single-grain weight by 14.55% (to 14.55 g) and panicle weight by 8.41% (to 1.65 kg), with lower within-treatment variation (Figure 2a). Longitudinal and transverse diameters were 4.25% and 5.18% larger than in the conventional treatment, respectively. The optimized treatment produced a higher sugar–acid ratio (16.73 vs. conventional), with sugar content 0.59 percentage points higher and organic acid content 0.03 percentage points lower. Optimized fertilization also produced more fruiting branches per plant (four on average) than the conventional treatment (Figure 2a).

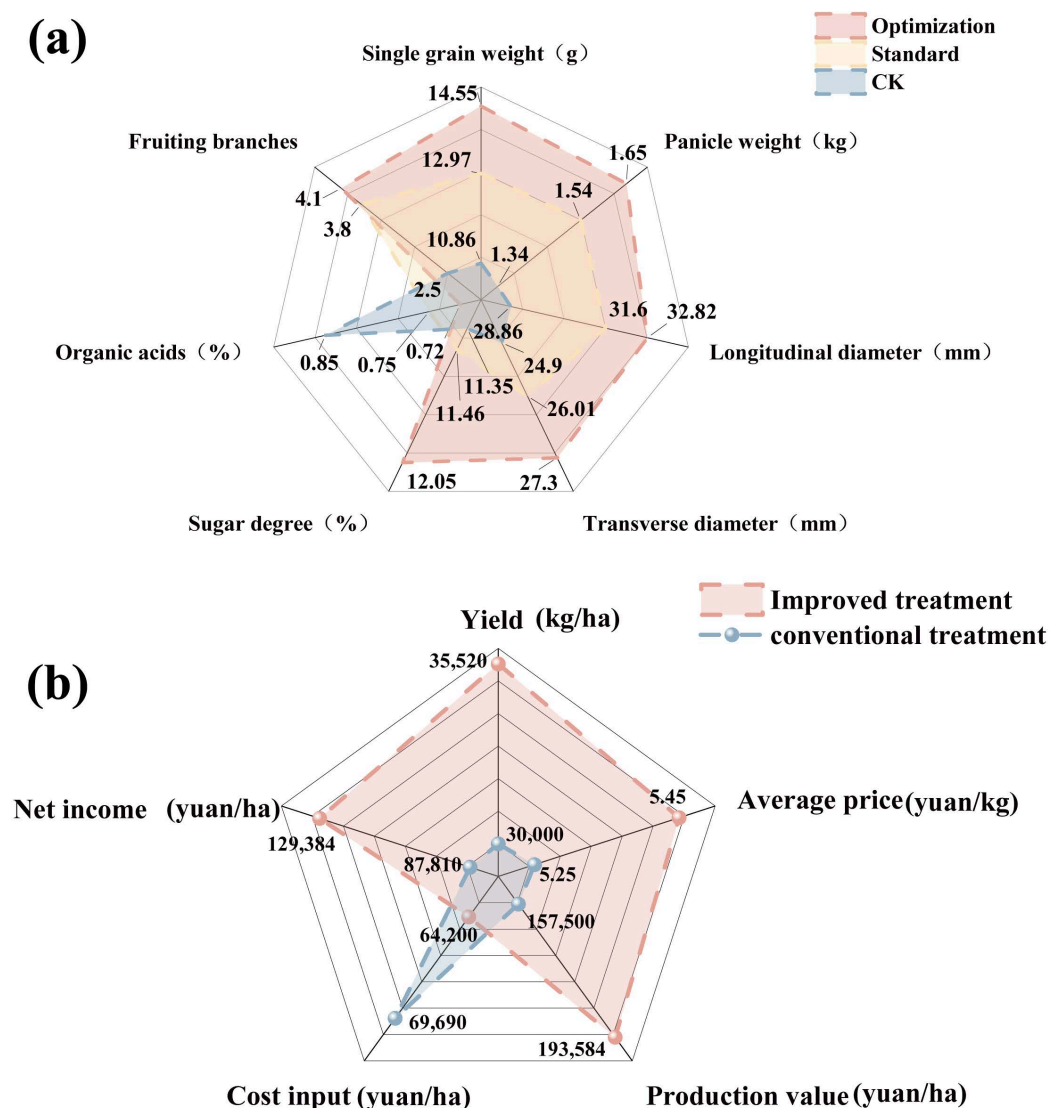


Figure 2. The plant growth traits of Red Globe Grapes in different fertilizer treatments. (a) Seven physiological indicators. (b) Five economic indicators.

Total nutrient input in the optimized treatment was lower by N 385.28 kg ha⁻¹, P₂O₅ 298.65 kg ha⁻¹, and K₂O 154.02 kg ha⁻¹, amounting to 837.95 kg ha⁻¹ less total fertilizer and a cost reduction of ¥5490 ha⁻¹ (Table 1). Yield under the optimized treatment averaged 35,520 kg ha⁻¹, an 18.40% increase over the conventional treatment. Selling price was also higher (¥5.45 vs. ¥5.25 kg⁻¹), reflecting improved quality. Output value rose by 22.91% (¥193,584 vs. ¥157,500 ha⁻¹). Pesticide and labor costs did not differ between treatments (¥15,000 ha⁻¹ each), so the net income gain from optimized fertilization was ¥41,574 ha⁻¹ (Figure 2b).

Table 1. Different fertilizer treatments of nutrient inputs and fertilizer costs.

Treatment	N	Nutrient Input P ₂ O ₅	K ₂ O	Fertilizer Cost (Yuan/ha)	N:P ₂ O ₅ :K ₂ O
Improved treatment	447.30	397.20	719.40	34,200	1:0.89:1.47
conventional treatment	832.58	695.85	873.42	39,690	1:0.84:1.05
Fertilizer saving	−385.28	−298.65	−154.02	−5490	/

3.3. Technical Readiness and Its Determinants

From 2016 to 2020, yield in the core area increased from approximately 35,400 to 52,500 kg ha^{−1} (+48%); in the coverage area, it increased from 30,400 to 48,400 kg ha^{−1} (+59%). Both areas showed a slight decline in 2020. In the development area, yield rose sharply in 2016–2017 (+31%), dropped in 2018, and recovered slowly thereafter, indicating greater interannual variability (Figure 3a).

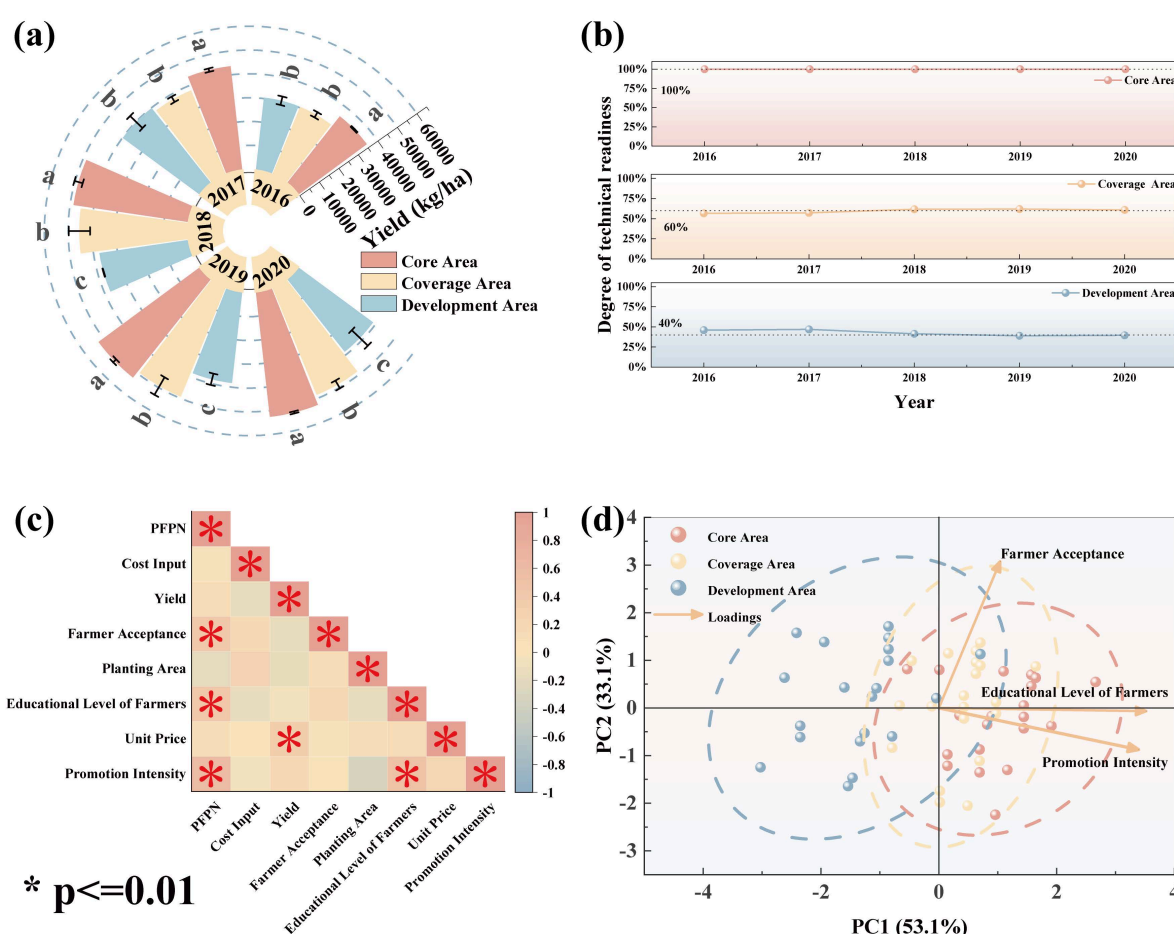


Figure 3. Technical readiness and analysis of the principal components of several key factors. (a) Yield trends in core, coverage, and development areas from 2016 to 2020. (b) Technical readiness (relative PFPN) over time. (c) Correlation matrix of eight agronomic and socio-economic indicators. The matrix displays pairwise Pearson correlation coefficients. Asterisks (*) indicate statistical significance at the $p \leq 0.01$ level (two-tailed). Variables include partial factor productivity of nitrogen (PFPN), cost input, grain yield, farmer acceptance, planting area, educational level of farmers, unit price, and promotion intensity. (d) Principal component analysis (PCA) biplot of farmer characteristics across three regional typologies. The score plot displays individual samples grouped into core, coverage, and development areas. Loading vectors represent the contribution of three explanatory variables: educational level, promotion intensity, and farmer acceptance. The direction and length of arrows indicate variable correlations and their influence on sample differentiation.

Relative PFPN (core = 100%) in 2016 was 56.6% in the coverage area and 46.1% in the development area. By 2020, coverage area PFPN reached approximately 60%, whereas development area PFPN had declined to 39.6% (Figure 3b).

PFPN correlated positively with yield and with farmer acceptance; cost input also correlated positively with acceptance (both $p \leq 0.01$; Figure 3c). Principal component analysis extracted two components with a cumulative variance of 86.2% (PC1: 53.1%, PC2: 33.1%). PC1 was primarily associated with yield, PFPN, and education level; PC2 was associated with promotion intensity and farmer acceptance. The score plot separated the three zones along PC1, with the core area in the positive quadrant, the development area in the negative quadrant, and the coverage area in between; PC2 further differentiated the relationship between promotion and acceptance (Figure 3d).

3.4. Spatial Spillover Effects and Attenuation Boundary

The SDM showed significant spatial dependence ($\text{Rho} = 0.5428$, $p = 0.012$; Table A3, Appendix A). Effect decomposition (Figure 4c) showed that farmer acceptance had a positive direct effect (1146.82) and a non-significant indirect spillover (7.73), despite a significant spatial lag term ($p = 0.012$). Education level had a non-significant negative direct effect (-73.19) but a large positive indirect spillover (2664.51), consistent with a highly significant spatial lag coefficient ($p < 0.001$). Promotion intensity had a significantly negative spatial lag term ($p = 0.042$), suggesting local crowding-out among neighbors; nevertheless, the net indirect effect, amplified by the spatial multiplier (Rho), was positive (3591.33).

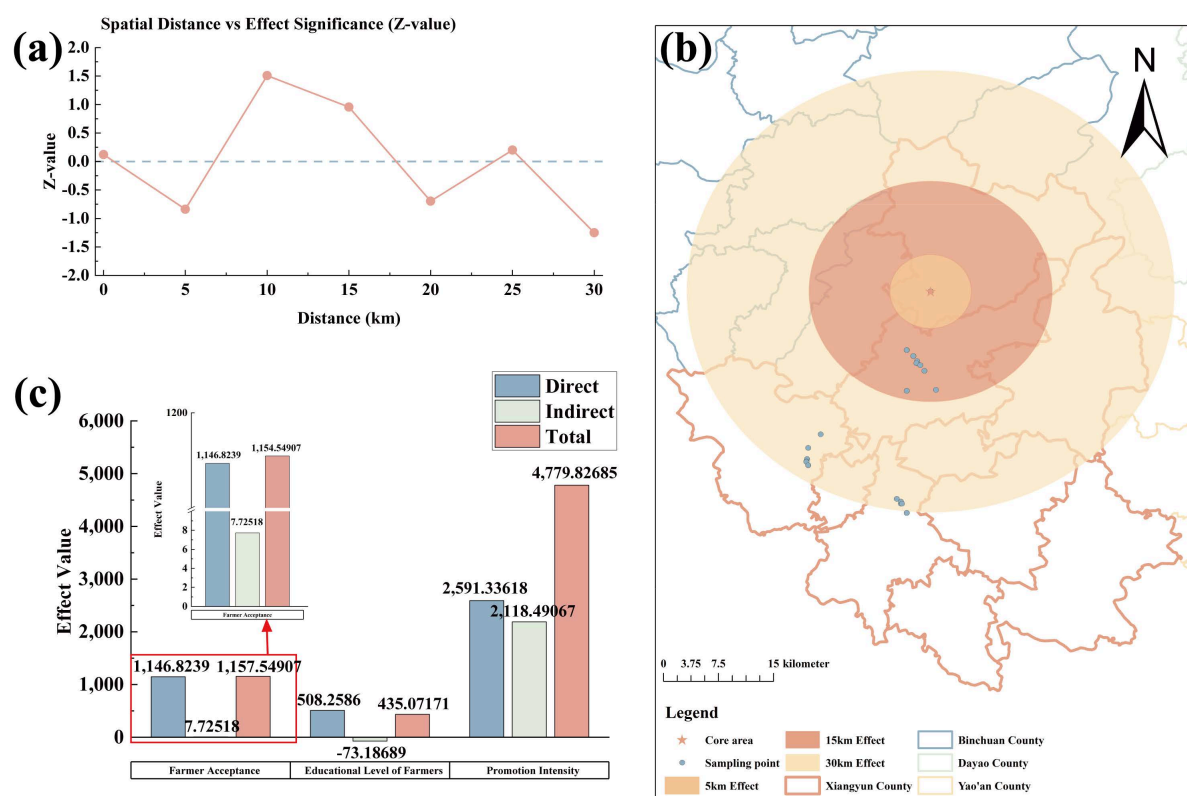


Figure 4. Spatial heterogeneity of the whole-process optimized fertilization. (a) Distance-decay curve of Z-values indicating significance attenuation. The Z-value represents the degree of standardization of residual differences within different distance intervals and can be used to measure the significance of spatial heterogeneity or spatial response intensity. (b) Radiation range map showing the core area, sampling points, and 5 km/15 km effect buffers across four counties. (c) Effect values of three explanatory variables (farmer acceptance, educational level, and promotion intensity).

The distance-decay analysis (Figure 4a) showed that spillover effects were strongest within 10 km, peaked between 10 and 17.5 km ($Z \approx 1.5$), and declined sharply thereafter, becoming non-significant beyond 30 km ($Z < -1.5$). Therefore, the attenuation boundary is at approximately 30 km and an optimal promotion radius is near 10 km. The radiation range map (Figure 4b) confirmed high-high clusters around the core area and low-low clusters in more distant zones.

Average yield growth rates across towns were HD 12.01%, XC 12.05%, MD 10.61%, and YNY 5.58%, suggesting that the optimized fertilization effect was smallest in YNY and its surrounding areas.

4. Discussion

Farmers' fertilization decisions in this survey responded to the previous year's grape price ($R^2 = 0.7702$) rather than to the attainable yield ($R^2 = 0.0058$). This disconnect between economic signals and agronomic needs is consistent with observations in other Chinese grape regions [29,30] and elsewhere [31]. The long production cycle of grapes creates a decision lag: farmers use past prices as a proxy for future returns [6]. While farmers may be aware of the negative effects of over-fertilization, social and economic factors perpetuate the practice [32]. Technical training alone is therefore unlikely to change behavior without complementary economic incentives.

The optimized plan reduced total nutrient input by 837.95 kg ha⁻¹ and increased yield by 18.4% and net income by ¥41,574 ha⁻¹. This aligns with "cost reduction and efficiency improvement" reported in other cropping systems [33], suggesting that phenology-based nutrient management is a transferable principle. The efficiency gain may arise from two mechanisms: reduced soil nutrient fixation and loss, which improve fertilizer recovery [34], and an improved root-zone water-nutrient environment that promotes uptake [35]. Thus, the optimized plan reconciles farmer economic objectives with agronomic sustainability, but only when correctly implemented.

Adoption, measured as relative PFPN (relative PFPN is an outcome-based metric used to distinguish between the implementation of the optimization plan and other factors that affect production or nitrogen input; therefore, it should be regarded as a performance proxy indicator), declined with distance from the core demonstration area. Coverage and core zones showed sustained yield gains over five years (+59% and +48%, respectively), whereas the development area exhibited unstable adoption and a drop in PFPN from 46.1% to 39.6% of the core benchmark. This spatial pattern conforms to the "distance decay" of technology diffusion [36,37]. The SDM estimates ($\text{Rho} = 0.5428$, $p = 0.012$) confirm significant spatial dependence. Spillover effects decayed beyond approximately 30 km, with an optimal promotion radius near 10 km.

Education level had a negative local direct effect but a large positive indirect spillover (2664.51), indicating that human capital externalities flow predominantly to neighboring areas rather than benefiting the adopter's own locality. This supports the "neighborhood effect" and observational learning mechanisms [38]. Promotion intensity showed local crowding-out (negative spatial lag, $p = 0.042$) but a net positive indirect effect (3591.33) after the spatial multiplier was applied, suggesting that competition among adjacent farmers is offset by cross-regional feedback. These divergent spatial effects imply that uniform extension strategies may be inefficient; region-specific approaches that leverage social networks are more likely to succeed [39].

Acceptance of the optimized technology correlated positively with adoption. Consistent with the Technology Acceptance Model [40], perceived usefulness—reinforced by visible yield gains in demonstration plots—appears to drive uptake. Effective scaling therefore requires a multi-stakeholder framework [41]. Demonstration networks within

the 15 km radius can build trust and facilitate transition from passive reception to active adoption [42]. Family farms and cooperatives may act as bridging actors [43]. Integrating government, university, enterprise, and farmer resources into a continuous service model—from training to market access—could further raise adoption rates [43,44]. However, the observed decline in adoption in development areas without ongoing support indicates that initial exposure is insufficient; sustained technical follow-up is necessary to prevent regression. Future work should test whether targeted support within the 15 km radius, combined with local educational investments, yields higher societal returns than uniform county-wide promotion.

These findings suggest that uniform county-wide promotion is unlikely to be efficient. Testing targeted support within the 10 km radius, against uniform promotion, would require an experiment designed with more spatial units. Future work should also measure adoption directly, rather than relying on PFPN as a proxy.

5. Conclusions

The optimized plan reduced N, P₂O₅, and K₂O inputs by 385.28, 298.65, and 154.02 kg ha^{−1}, respectively; increased yield by 18.4%; and raised net income by 41,574 RMB ha^{−1} relative to conventional practices. After five years of promotion, technical readiness (PFPN) was highest in the core demonstration area and declined with distance; the development area did not sustain the initial adoption gains. The spatial attenuation boundary was approximately 30 km, with an optimal promotion radius near 10 km. Farmer education had strong positive spatial spillovers, whereas promotion intensity showed local competitive crowding-out that was more than offset by positive cross-regional feedback. Scaling optimized fertilization in county-level grape systems therefore requires spatially differentiated extension that strengthens social learning in neighboring areas and reduces reliance on uniform promotional intensity.

Author Contributions: C.X.: Writing—original draft, Methodology, Investigation, Formal analysis, Data curation. R.M.: Writing—review and editing, Funding acquisition, Conceptualization. H.W.: Writing—original draft, Methodology, Investigation, Formal analysis. C.B.: Methodology, Investigation, Data curation. T.L.: Methodology, Investigation, Data curation. Z.C.: Methodology, Investigation, Conceptualization. Y.W.: Writing—review and editing, Supervision. Z.X.: Writing—review and editing, Writing—original draft, Supervision, Investigation, Funding acquisition, Conceptualization. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the International Joint Laboratory Project for Resource Utilization of Agricultural Solid Waste in Yunnan Province (202503AP140009), the National Key Research and Development Program of China (2022YFD1901500/2022YFD1901504), the Major Science and Technology Special Project of Yunnan Province (202302AE090012, 202302AE090009), the National Natural Science Foundation of China (32160744), and the Top Young Talents of Yunnan High-level Talent Training and Support Program (YNWR-QNBJ-2019-249). The APC was funded by Zhi Xu.

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

Acknowledgments: The authors have reviewed and edited the output and take full responsibility for the content of this publication.

Conflicts of Interest: The authors declare no conflicts 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.

Abbreviations

The following abbreviations are used in this manuscript:

Red Globe Grapes	<i>Vitis vinifera</i> ‘Red Globe’
TRL	Technology Readiness Level
PFPN	Partial factor productivity of nitrogen
SDM	The Spatial Durbin Model
ANOVA	One-way analysis of variance
PCA	Principal component analysis
YNY	Yunnanyi Town
XC	Xiangcheng Town
HD	Hedian Town
MD	Midian Town

Appendix A

Table A1. The design of the farmer conventional fertilization scheme. Based on the previous year’s fertilizer application survey results, the fertilizer application plan is designed, and the fertilizer amount in each application period is the total amount of fertilizer in this period.

Fertilization Period	Fertilizer Application (kg/ha)	Number of Applications
Pre-budbreak	Ammonium dihydrogen phosphate (12-61-0) 150 kg, Rooting powder 75 kg, Boron fertilizer 7.5 kg, Zinc fertilizer 4.5 kg	1
From budbreak to pre-bloom	Ammonium dihydrogen phosphate (12-61-0) 255 kg, Rooting powder 75 kg, 20-20-20 + TE 450 kg, Urea 135 kg, Boron fertilizer 15 kg + Zinc fertilizer 9 kg (supplemented twice)	4 (at 10-day intervals)
From bloom onset to end of bloom	Boron fertilizer 40g, Zinc fertilizer 0.6 kg (Foliar spray)	1
From fruit set to pre-veraison	Ammonium dihydrogen phosphate (12-61-0) 30 kg, 20-20-20 + TE 975 kg, Urea 420 kg, Boron fertilizer 7.5 kg + Zinc fertilizer 4.5 kg (supplemented once), Calcium ammonium nitrate 60 kg + Magnesium sulfate 30 kg (supplemented once)	6 (at 10-day intervals)
From veraison to pre-harvest	20-20-20 + TE 450 kg, 10-8-42 + TE 150 kg, Ammonium dihydrogen phosphate 225 kg, Potassium sulfate 225 kg, Potassium nitrate 450 kg, Urea 60 kg	7 (at 7-day intervals)

Table A2. The design of improved fertilization. Based on grape nutrient requirements and distribution patterns, the farmer’s conventional fertilizer, supplemented with ammonium nitrate and magnesium sulfate fertilizer for optimized combination, was selected, and the optimized fertilization plan was designed. The fertilizer application in each fertilization period details the total amount of fertilizer used in this period.

Fertilization Period	Fertilizer Application (kg/ha)	Number of Applications
From budbreak to pre-bloom	16-16-16 + TE 300 kg, Potassium dihydrogen phosphate 90 kg, 20-20-20 + TE 120 kg calcium ammonium nitrate 120 kg + magnesium sulfate 60 kg (supplemented twice) Boron fertilizer 7.5 kg + Zinc fertilizer 4.5 kg (supplemented once)	4 (at 10-day intervals)
From bloom onset to end of bloom	Boron fertilizer 0.6 kg, Zinc fertilizer 0.6 kg (Foliar spray)	1
From fruit set to pre-veraison	20-20-20 + TE 525 kg, 10-8-42 + TE 450 kg, Potassium dihydrogen phosphate 120 kg calcium ammonium nitrate 60 kg + magnesium sulfate 30 kg (supplemented once) Boron fertilizer 7.5 kg + Zinc fertilizer 4.5 kg (supplemented once)	6 (at 10-day intervals)

Table A2. *Cont.*

Fertilization Period	Fertilizer Application (kg/ha)	Number of Applications
From veraison to pre-harvest	20-20-20 + TE 150 kg, 10-8-42 + TE 600 kg, Potassium dihydrogen phosphate 90 kg calcium ammonium nitrate 120 kg + magnesium sulfate 60 kg (supplemented twice) Boron fertilizer 7.5 kg + Zinc fertilizer 4.5 kg (supplemented once)	7 (at 7-day intervals)
Fertilization Period	Fertilizer Application (kg/ha)	Number of Applications

Table A3. The Spatial Durbin Model estimation results.

	Coefficient Estimate	Standard Error	z	p	Significance
Intercept	−80,325.871	31,110.101	−2.582	0.0098	**
Farmer Acceptance	1616.339	825.224	1.959	0.0502	*
Educational Level of Farmers	190.993	789.125	0.242	0.8088	
Promotion Intensity	−66.869	648.660	−0.103	0.9179	
lag. Farmer Acceptance	11,509.588	4584.343	2.511	0.0121	**
lag. Educational Level of Farmers	23,858.800	7104.212	3.358	0.0008	***
lag. Promotion Intensity	−6415.881	3161.069	−2.030	0.0424	*
Spatial lag coefficient Rho	0.5428	0.21833	2.486	0.0129	**

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A4. Farmers' Tracking Survey Form.

Farmer Name	Information	Village	Duration	Yield	Frame Type
Variety	Area	Income	Density	Remarks	Total Nutrient
Period	Date	Pesticide and Fertilizer Usage Statistics		N	P ₂ O ₅ K

Figure A1 is a collection of photographs (a–c) taken by the authors during the 2016–2020 promotion period. The panels show (a) an on-farm demonstration plot; (b) a one-on-one farmer consultation; and (c) a group training session.

Table A5. Decomposition results of variable space effect. The direct effect, indirect effect and total effect of the main variables are shown.

Variable Quantity	Direct Effect	Indigo Effect	Gross Effect
Farmer Acceptance	1146.823895	7.725178	1154.549074
Educational Level of Farmers	508.258599	−73.186892	435.071707
Promotion Intensity	2591.33618	2188.490668	4779.826847

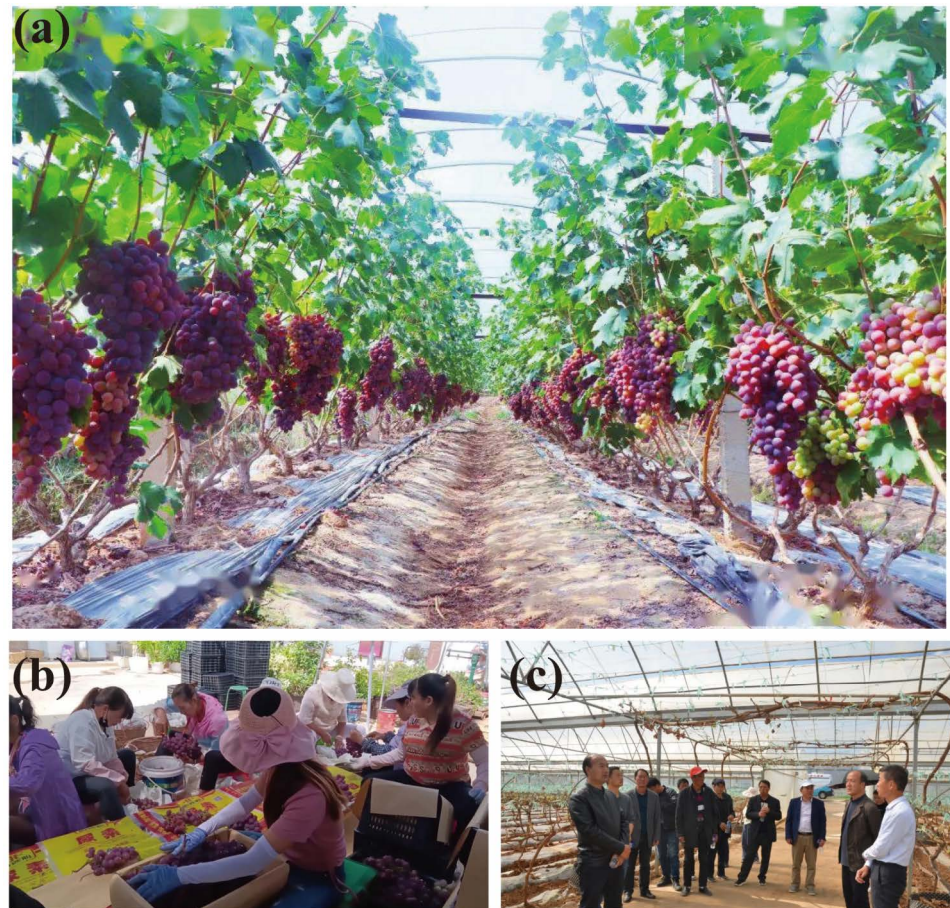


Figure A1. Promotional activities for the whole-process optimized fertilization plan in Xiangyun County, 2016–2020. (a) On-farm demonstration; (b) one-on-one consultation; (c) group training.

References

1. Li, X.; Yang, F.; Li, B.; Li, Y.; Sun, R.; Li, B. Research Progress and Prospects of Mechanized Planting Technology and Equipment for Wine Grapes. *Agronomy* **2025**, *15*, 1207. [[CrossRef](#)]
2. Kong, X.; Yang, F.; Huang, Q.; Fang, F.; Guo, Y.; Zou, Q.; Luo, H.; Yu, L. Comparative Profiling of Aroma Volatiles and Flavonoid Biosynthesis in Crimson Seedless, Red Globe, and Shine Muscat Table Grapes Using GC-IMS and RNA-Seq. *Foods* **2026**, *15*, 823. [[CrossRef](#)] [[PubMed](#)]
3. Wang, X.; Xie, X.; Chen, N.; Wang, H.; Li, H. Study on current status and climatic characteristics of wine regions in China. *VITIS J. Grapevine Res.* **2018**, *57*, 9–16. [[CrossRef](#)]
4. Ohana-Levi, N.; Netzer, Y. Long-Term Global Trends in Vineyard Coverage and Fresh Grape Production. *Agriculture* **2025**, *15*, 1976. [[CrossRef](#)]
5. Zhao, C.; Wu, Y.; Luo, Z.; Zhao, T.; Zhang, R.; Wang, Y. Contrasting temporal responses of growth, photosynthesis and antioxidant defence to nitrogen supply in two table grape cultivars. *Plant Physiol. Biochem.* **2026**, *238*, 111594. [[CrossRef](#)] [[PubMed](#)]
6. Chen, H.; Yang, J.; Deng, X.; Lei, Y.; Xie, S.; Guo, S.; Ren, R.; Li, J.; Zhang, Z.; Xu, T. Foliar-sprayed manganese sulfate improves flavonoid content in grape berry skin of Cabernet Sauvignon (*Vitis vinifera* L.) growing on alkaline soil and wine chromatic characteristics. *Food Chem.* **2020**, *314*, 126182. [[CrossRef](#)] [[PubMed](#)]
7. Tian, Y.; Wang, Q.; Zhang, W.; Gao, L. Reducing environmental risk of excessively fertilized soils and improving cucumber growth by *Caragana microphylla*-straw compost application in long-term continuous cropping systems. *Sci. Total Environ.* **2016**, *544*, 251–261. [[CrossRef](#)] [[PubMed](#)]
8. Guo, J.H.; Liu, X.J.; Zhang, Y.; Shen, J.L.; Han, W.X.; Zhang, W.F.; Christie, P.; Goulding, K.W.T.; Vitousek, P.M.; Zhang, F.S. Significant Acidification in Major Chinese Croplands. *Science* **2010**, *327*, 1008–1010. [[CrossRef](#)] [[PubMed](#)]
9. An, Z.; Wang, C.; Jiao, X.; Kong, Z.; Jiang, W.; Zhang, D.; Ma, W.; Zhang, F. Methodology of Analyzing Maize Density Loss in Smallholder's Fields and Potential Optimize Approach. *Agriculture* **2021**, *11*, 480. [[CrossRef](#)]
10. Yu, C.; Huang, X.; Chen, H.; Godfray, H.C.J.; Wright, J.S.; Hall, J.W.; Gong, P.; Ni, S.; Qiao, S.; Huang, G.; et al. Managing nitrogen to restore water quality in China. *Nature* **2019**, *567*, 516–520. [[CrossRef](#)] [[PubMed](#)]

11. Chen, X.; Cui, Z.; Fan, M.; Vitousek, P.; Zhao, M.; Ma, W.; Wang, Z.; Zhang, W.; Yan, X.; Yang, J.; et al. Producing more grain with lower environmental costs. *Nature* **2014**, *514*, 486–489. [[CrossRef](#)] [[PubMed](#)]
12. Chen, X.-P.; Cui, Z.-L.; Vitousek, P.M.; Cassman, K.G.; Matson, P.A.; Bai, J.-S.; Meng, Q.-F.; Hou, P.; Yue, S.-C.; Römheld, V.; et al. Integrated soil–crop system management for food security. *Proc. Natl. Acad. Sci. USA* **2011**, *108*, 6399–6404. [[CrossRef](#)] [[PubMed](#)]
13. Xu, X.; He, P.; Pampolino, M.F.; Li, Y.; Liu, S.; Xie, J.; Hou, Y.; Zhou, W. Narrowing yield gaps and increasing nutrient use efficiencies using the Nutrient Expert system for maize in Northeast China. *Field Crops Res.* **2016**, *194*, 75–82. [[CrossRef](#)]
14. Xu, X.; Xiao, C.; Bi, R.; Jiao, Y.; Wang, B.; Dong, Y.; Xiong, Z. Optimizing organic fertilization towards sustainable vegetable production evaluated by long-term field measurement and multi-level fuzzy comprehensive model. *Agric. Ecosyst. Environ.* **2024**, *368*, 109008. [[CrossRef](#)]
15. Wang, X.; Shao, X.; Zhang, Z.; Zhong, X.; Ji, X.; Shi, X.; Liu, C.; Wang, Z.; Liu, F.; Wang, H. Multi-nutrient fertilization-based analysis of fruit quality and mineral element composition during fruit development in Merlot wine grapevines. *J. Integr. Agric.* **2025**, *24*, 1503–1514. [[CrossRef](#)]
16. Liu, M.; Wang, X.; Yang, B.; Song, D.; Xu, X.; Ding, W.; He, P.; Zhou, W. Optimized fertilization strategies enhanced integrated benefits in nutrient management for open-field cabbage production. *J. Agric. Food Res.* **2025**, *20*, 101801. [[CrossRef](#)]
17. Lucchetta, M.; Pii, Y.; Cagnin, A.; Lovat, L.; Romano, A.; Correddu, F.; Gaiotti, F. *Controlled-Release Nitrogen Technology as a Sustainable Nutrition Management in Lean-Soil Vineyards*; International Society for Horticultural Science (ISHS): Leuven, Belgium, 2024; pp. 135–142.
18. Garlet, L.P.; Moura-Bueno, J.M.; Tassinari, A.; Kokkonen, A.A.; Papalia, D.G.; Marques, A.L.; Schemmer, S.; de Souza, B.E.; Michelato, B.; de Araújo Pedron, F.; et al. The Fate of Potassium in Southern Brazilian Vineyards. *J. Soil Sci. Plant Nutr.* **2025**, *25*, 6494–6507. [[CrossRef](#)]
19. Hallaç Türk, F.; Kurt, A. The effects of plant and animal-derived aminoacid and humic acid-based biostimulants on yield and quality in the wine grape. *Front. Plant Sci.* **2025**, *16*. [[CrossRef](#)] [[PubMed](#)]
20. Zhang, T.; Hou, Y.; Meng, T.; Ma, Y.; Tan, M.; Zhang, F.; Oenema, O. Replacing synthetic fertilizer by manure requires adjusted technology and incentives: A farm survey across China. *Resour. Conserv. Recycl.* **2021**, *168*, 105301. [[CrossRef](#)]
21. Schut, M.; Leeuwis, C.; Thiele, G. Science of Scaling: Understanding and guiding the scaling of innovation for societal outcomes. *Agric. Syst.* **2020**, *184*, 102908. [[CrossRef](#)]
22. Wang, X.; Dou, Z.; Shi, X.; Zou, C.; Liu, D.; Wang, Z.; Guan, X.; Sun, Y.; Wu, G.; Zhang, B.; et al. Innovative management programme reduces environmental impacts in Chinese vegetable production. *Nat. Food* **2021**, *2*, 47–53. [[CrossRef](#)] [[PubMed](#)]
23. Lezama-Nicolás, R.; Rodríguez-Salvador, M.; Río-Belver, R.; Bildosola, I. A bibliometric method for assessing technological maturity: The case of additive manufacturing. *Scientometrics* **2018**, *117*, 1425–1452. [[CrossRef](#)] [[PubMed](#)]
24. Ozcan, S.; Stornelli, A.; Simms, C. A Product Innovation Readiness Level Framework. *IEEE Trans. Eng. Manag.* **2024**, *71*, 9920–9937. [[CrossRef](#)]
25. Vik, J.; Melås, A.M.; Stræte, E.P.; Søråa, R.A. Balanced readiness level assessment (BRLa): A tool for exploring new and emerging technologies. *Technol. Forecast. Soc. Change* **2021**, *169*, 120854. [[CrossRef](#)]
26. Miller, H.J. Tobler’s First Law and Spatial Analysis. *Ann. Assoc. Am. Geogr.* **2004**, *94*, 284–289. [[CrossRef](#)]
27. Zhu, Y.-J.; Hu, Y.; Collins, J.M. Estimating road network accessibility during a hurricane evacuation: A case study of hurricane Irma in Florida. *Transp. Res. Part D Transp. Environ.* **2020**, *83*, 102334. [[CrossRef](#)]
28. Luo, P.; Song, Y.; Zhu, D.; Cheng, J.; Meng, L. A generalized heterogeneity model for spatial interpolation. *Int. J. Geogr. Inf. Sci.* **2023**, *37*, 634–659. [[CrossRef](#)]
29. Chen, R.; Chang, H.; Wang, Z.; Lin, H. Determining organic-inorganic fertilizer application threshold to maximize the yield and quality of drip-irrigated grapes in an extremely arid area of Xinjiang, China. *Agric. Water Manag.* **2023**, *276*, 108070. [[CrossRef](#)]
30. Xue, C.; Zhang, T.; Yao, S.; Guo, Y. Effects of Households’ Fertilization Knowledge and Technologies on Over-Fertilization: A Case Study of Grape Growers in Shaanxi, China. *Land* **2020**, *9*, 321. [[CrossRef](#)]
31. Oliveira da Silva, A.; Silva Costa, B.R.; Oldoni, H.; José Silva, D.; Bassoi, L.H. Potassium fertigation and organic fertilisation in ‘Syrah’ grape in Northeastern Brazil: Yield, must characteristics and phenolic compounds. *OENO One* **2024**, *58*. [[CrossRef](#)]
32. McDonald, A.J.; Balwinder, S.; Keil, A.; Srivastava, A.; Craufurd, P.; Kishore, A.; Kumar, V.; Paudel, G.; Singh, S.; Singh, A.K.; et al. Time management governs climate resilience and productivity in the coupled rice–wheat cropping systems of eastern India. *Nat. Food* **2022**, *3*, 542–551. [[CrossRef](#)] [[PubMed](#)]
33. Yang, J.; Su, K.; Zhang, Z.; Guo, S.; Hou, Y.; Wen, Y. Perceived Benefit, Policy Incentive and Farmers’ Organic Fertilizer Application in Protected Areas. *Agriculture* **2024**, *14*, 810. [[CrossRef](#)]
34. James, A.; Mahinda, A.; Mwamahonje, A.; Rweyemamu, E.W.; Mrema, E.; Aloys, K.; Swai, E.; Mpore, F.J.; Massawe, C. A review on the influence of fertilizers application on grape yield and quality in the tropics. *J. Plant Nutr.* **2023**, *46*, 2936–2957. [[CrossRef](#)]
35. Li, Q.; Andom, O.; Li, Y.; Cheng, C.; Deng, H.; Sun, L.; Li, Z. Responses of grape yield and quality, soil physicochemical and microbial properties to different planting years. *Eur. J. Soil Biol.* **2024**, *120*, 103587. [[CrossRef](#)]

36. Chen, X.; Li, T. Diffusion of Agricultural Technology Innovation: Research Progress of Innovation Diffusion in Chinese Agricultural Science and Technology Parks. *Sustainability* **2022**, *14*, 15008. [[CrossRef](#)]
37. Zhao, X.; Jiang, S.; Gao, J. Spatial impacts of Green Finance Reform Pilot Zones on renewable energy technology innovation: Pathways for accelerating low-altitude economic development. *Renew. Energy* **2025**, 125023. [[CrossRef](#)]
38. Lee, G.; Sawadogo-Compaoré, E.M.F.W.; Ikazaki, K.; Muraoka, R. The Adoption and Dissemination of Soil Conservation Technologies Among Sorghum Farmers in Burkina Faso: Perspectives on Innovation, Network, and Risk Aversion. *Land Degrad. Dev.* **2025**. [[CrossRef](#)]
39. Lin, M.; Peng, B. Does regional coordinated development enhance urban resilience? Evidence from China's Beijing-Tianjin-Hebei region. *Econ. Anal. Policy* **2025**, *87*, 1232–1261. [[CrossRef](#)]
40. McCormack, M.; Buckley, C.; Kelly, E. Using a Technology Acceptance Model to investigate what factors influence farmer adoption of a nutrient management plan. *Ir. J. Agr. Food Res.* **2021**, *60*, 142–151. [[CrossRef](#)]
41. Liu, Z.; Ding, R.; Wang, L.; Song, R.; Song, X. Cooperation in an uncertain environment: The impact of stakeholders' concerted action on collaborative innovation projects risk management. *Technol. Forecast. Soc. Change* **2023**, *196*, 122804. [[CrossRef](#)]
42. An, Z.; Yang, Y.; Yang, X.; Ma, W.; Jiang, W.; Li, Y.; Chen, G.; Zhang, W.; Zhuang, M.; Wang, C.; et al. Promoting sustainable smallholder farming via multistakeholder collaboration. *Proc. Natl. Acad. Sci. USA* **2024**, *121*, e2319519121. [[CrossRef](#)] [[PubMed](#)]
43. Amoabeng-Nimako, S.; Ingenbleek, P.T.M.; Dittoh, S.; Gouzaye, A.; Bindraban, P. Designing an incentive system to promote the adoption of sustainable soil health management practices among smallholder farmers in northern Ghana. *Land Use Policy* **2026**, *161*, 107847. [[CrossRef](#)]
44. Wu, X.; Chen, S. Integrating farmers into residents: A multi-dimensional textual analysis of China's poverty alleviation through relocation policy in urban resettlement. *Cities* **2025**, *165*, 106151. [[CrossRef](#)]

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.