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Peer Review File

Cropland concentration powers sustainable intensification of agriculture in China

Corresponding Author: Professor Shibin Liu

This manuscript has been previously reviewed at another journal. This document only contains information relating to versions considered at Communications Earth & Environment.

This file contains all editorial decision letters in order by version, followed by all author rebuttals in order by version.

Attachments originally included by the reviewers as part of their assessment can be found at the end of this file.

Version 0:

Decision Letter:

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Dear Professor Liu,

Please allow me to apologize again for sending this delayed decision on your manuscript titled "Cropland concentration powers sustainable intensification of agriculture in China". It has now been seen by 2 reviewers, whose comments are appended below. You will see that they find your work of some potential interest. However, they have raised quite substantial concerns that must be addressed. In light of these comments, we cannot accept the manuscript for publication, but would be interested in considering a revised version that fully addresses these serious concerns.

In revision, please address the editorial thresholds as follows:

** Provide a compelling analysis of how cropland concentration contributes to sustainable agricultural intensification in China, including thorough discussions on potential factors influencing agricultural intensification and clear explanations of advantages of the remote sensing product.

** Make a full analysis of uncertainties in the input data and a clarification of data selection, providing robust findings.

** Clearly explain terms (i.e., agricultural intensification) and methods (i.e., the Freedman-Diaconis rule) used in the study so that readers can easily understand the analysis.

We hope you will find the reviewers' comments useful as you decide how to proceed. Should additional work allow you to address these criticisms, we would be happy to look at a substantially revised manuscript. If you choose to take up this option, please either highlight all changes in the manuscript text file, or provide a list of the changes to the manuscript with your responses to the reviewers.

When resubmitting, please provide a point-by-point response to the reviewers' comments. Please submit your responses as a separate file, distinct from your cover letter where you can add responses to the Editors' comments that you do not want to be made available to the reviewers. Word files are preferred. We recommend that any figures, tables or graphs that are included in the response to reviewers are also included in the main article or Supplementary Information.

Please bear in mind that we will be reluctant to approach the reviewers again in the absence of substantial revisions.

If the revision process takes significantly longer than three months, we will be happy to reconsider your paper at a later date, as long as nothing similar has been accepted for publication at Communications Earth & Environment or published elsewhere in the meantime.

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Please do not hesitate to contact us if you have any questions or would like to discuss the required revisions further. Thank you for the opportunity to review your work.

Best regards,

Mengjie Wang
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REVIEWER COMMENTS:

Reviewer #1 (Remarks to the Author):

The manuscript offers an interesting analysis of cropland distribution and agricultural intensification trends in China over the past two decades, using a dataset compiled from Google Earth Engine and Landsat imagery. The study's findings on cropland concentration and its role in sustainable intensification provide valuable insights into China's agricultural future. However, there are several areas that require major revision for the paper to meet the standards of a high-quality publication. Below are my detailed comments:

1. The introduction is somewhat repetitive and could benefit from a more concise and focused presentation. Key concepts are introduced, but the central aim of the study and its innovative contribution are not immediately clear. The section could be streamlined to emphasize the specific knowledge gap that the study addresses—namely, how cropland concentration contributes to sustainable agricultural intensification in China.

2. The manuscript relies on data from only five years (2000, 2005, 2010, 2015, 2020), yet the authors discuss a 20-year analysis period. This choice raises questions regarding the sufficiency of the data, as the representation of trends may be limited by the gap between these data points. The authors should clarify why these specific years were chosen over continuous or more frequent sampling, and whether this selection affects the robustness of the study's conclusions. Additionally, the use of the term "5-phase" to describe the analysis could be misleading, as it implies continuous data rather

than discrete time points. A clearer explanation of this terminology is needed.

3. The statement regarding the sharing of advanced agricultural technologies with low-yielding countries (lines 77-79) seems tangential to the core focus of the paper. It does not directly support the study's main argument about cropland concentration and sustainable intensification in China.

4. In the “Potential and challenges for sustainable intensification of agriculture in China” session, the authors briefly mention government reforms related to agricultural water use, but this aspect is not discussed in the body of the paper. Given the critical role of irrigation in agricultural intensification, it would be beneficial to incorporate irrigation as an additional input factor in the analysis. The authors could explore its role in shaping agricultural sustainability alongside the changes in fertilizer and machinery inputs. Including this factor would enhance the depth and comprehensiveness of the study.

5. Figure 5 presents data without significant analysis or interpretation and feels more suited for the appendix rather than the main body of the manuscript. The figure does not provide substantial explanatory value in its current form and should either be reworked to provide more analytical insights or moved to the supplementary material to avoid detracting from the narrative.

6. This paper focus on historical and current trends but do not explore potential future trajectories of cropland concentration and its effects on sustainable intensification. The inclusion of projections or simulations that model the potential long-term impacts of cropland concentration would make the study more forward-looking and robust. This would strengthen the paper's argument for the sustainability of agricultural intensification under the current trajectory of cropland concentration.

7. While the dataset used in the study is extensive, the selection of only five years leaves room for concern about the representativeness and robustness of the findings. The authors should address whether this limited temporal coverage might overlook short-term fluctuations or fail to capture more granular trends. A more detailed explanation of the rationale for this data selection, including any potential limitations, would improve the paper’s transparency and reliability.

8. The term "agricultural intensification" is frequently used but would benefit from a more explicit definition. It is not clear whether the term refers exclusively to technological inputs, crop yields, or other socio-economic factors. A clearer definition would help readers understand the scope of the study and the specific aspects of intensification that are being analyzed.

9. The article lacks an analysis of the uncertainty in the input data and how this uncertainty propagates in the calculations. Given the complexity of agricultural systems and potential measurement errors, assessing how these uncertainties affect the results is crucial. A detailed uncertainty analysis would help quantify potential variations in the results, providing a clearer understanding of the reliability and robustness of the conclusions. Without such analysis, the findings might be interpreted too confidently, especially when applied to policy or agricultural planning.

This study provides valuable insights into the dynamics of cropland concentration in China and its potential to drive sustainable agricultural intensification. However, several issues related to the data selection, conceptual clarity, and the integration of additional agricultural inputs (such as irrigation) need to be addressed. The authors should also consider expanding their analysis to include future projections of cropland concentration, which would strengthen the paper's argument for the sustainability of agricultural intensification in China. With these revisions, the manuscript has the potential to make a significant contribution to the field of agricultural sustainability.

Reviewer #2 (Remarks to the Author):

This manuscript applies well-established methods and datasets to validate an intuitively reasonable hypothesis rather than providing novel theoretical insights or methodological innovations. While the study offers a detailed analysis of cropland distribution and sustainable intensification using remote sensing and machine learning techniques, the approach—including RF classification, vegetation indices, and spatial-temporal analysis—is widely documented in the literature. The findings, though informative, primarily confirm expected trends rather than addressing an unresolved research gap.

Major Concerns:
1. The study follows conventional workflows without introducing substantial methodological advancements. It primarily validates known patterns rather than proposing a new framework or addressing a critical gap in sustainable intensification research. The authors should consider whether the study could go beyond confirming expected trends to tackle an unresolved challenge in agricultural intensification.
2. The use of the Freedman-Diaconis rule for defining change patterns in landscape indices and agricultural production indicators raises concerns. This rule is traditionally used for histogram binning, and its application to classify agricultural change patterns—especially with spatial-temporal variations—needs further justification. How does it account for the temporal dynamics and spatial heterogeneity of agricultural change?
3. The classification of agricultural regions is inconsistent. While the study initially divides China into nine agricultural production zones, Fig. 3 presents results at the provincial level. The rationale behind this discrepancy should be clarified.
4. The study generates cropland maps across five periods but does not justify why existing cropland datasets were not used. If the newly created maps offer higher classification accuracy, this advantage should be explicitly demonstrated rather than assumed based on similarity with previous results.

Additional Comments:

1. The introduction provides a strong background on food security and agricultural intensification but could be better structured. A suggested logical flow:
i. Global food security challenges and agricultural intensification
ii. Environmental concerns related to intensification
iii. China's specific situation (e.g., excessive chemical use, fragmented farmland)
iv. Limitations of current evaluation methods and the need for remote sensing
v. Research gap and contributions of this study
2. Abbreviations: Once an acronym is introduced, the full term should not be repeated.
3. Supplementary Fig. 4 appears to be a direct screenshot from GEE's console, which seems unpolished. A more refined presentation is recommended.
4. Figs. 1 & 4: High-saturation colors should be avoided for clarity.

Version 1:

Decision Letter:

** Please ensure you delete the link to your author home page in this e-mail if you wish to forward it to your coauthors **

Dear Professor Liu,

Your manuscript titled "Cropland concentration powers sustainable intensification of agriculture in China" has now been seen by 2 reviewers, and we include their comments at the end of this message. They find your work of interest, but some important points are still raised by reviewer #1. We are interested in the possibility of publishing your study in Communications Earth & Environment, but would like to consider your responses to these concerns and assess a revised manuscript before we make a final decision on publication.

In the revision, please provide a thorough analysis of uncertainties in your methods and their impact on conclusions, as raised by reviewer #1.

We therefore invite you to revise and resubmit your manuscript, along with a point-by-point response that takes into account the points raised. Please highlight all changes in the manuscript text file.

Please submit your point-by-point responses as a separate file, distinct from your cover letter where you can add responses to the Editors' comments that you do not want to be made available to the reviewers. Word files are preferred. We recommend that any figures, tables or graphs that are included in the response to reviewers are also included in the main article or Supplementary Information.

We are committed to providing a fair and constructive peer-review process. Please don't hesitate to contact us if you wish to discuss the revision in more detail.

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We hope to receive your revised paper within six weeks; please let us know if you aren't able to submit it within this time so that we can discuss how best to proceed. If we don't hear from you, and the revision process takes significantly longer, we may close your file. In this event, we will still be happy to reconsider your paper at a later date, as long as nothing similar has been accepted for publication at Communications Earth & Environment or published elsewhere in the meantime.

Please do not hesitate to contact us if you have any questions or would like to discuss these revisions further. We look forward to seeing the revised manuscript and thank you for the opportunity to review your work.

Best regards,

Mengjie Wang

Associate Editor, Communications Earth & Environment
Consulting Editor, Communications Sustainability
Bluesky: @commsearth.nature.com; @commssustain.nature.com

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REVIEWER COMMENTS:

Reviewer #1 (Remarks to the Author):

Thank you for the revisions and the additional clarifications you provided in your response. I have reviewed the manuscript again, and I would like to offer feedback on two critical aspects that were raised previously but have not been fully addressed. While your paper offers valuable insights into agricultural intensification, there are several areas that require further refinement to strengthen the robustness and relevance of the study.

1. Uncertainty analysis of input data

In the earlier round of review, it was emphasized that an analysis of the uncertainty in the input data and its propagation through the calculations is essential. This is particularly important in agricultural systems, where measurement errors and model assumptions can significantly influence the study's conclusions.

Although your response acknowledged this concern, the revised manuscript does not provide a detailed uncertainty analysis. The current version presents the results without clearly quantifying how uncertainties in the data, such as spatial resolution mismatches or measurement errors, might impact the conclusions. A thorough uncertainty analysis would be instrumental in assessing the reliability and robustness of your findings, offering a more nuanced interpretation.

2. Future projections and trajectories of cropland concentration

While your manuscript focuses on historical trends and current data, incorporating future projections or simulations that model the long-term impacts of cropland concentration is an essential aspect that has not been fully addressed. Including projections would not only make the study more forward-looking but also provide valuable insights into the sustainability of agricultural intensification under future scenarios.

You raised valid concerns regarding the mismatch in spatial resolution between the historical data (30m resolution) and the future simulation datasets (1 km resolution). However, the response did not explore sufficiently alternative methods or techniques to address this issue. For example, simulations could be conducted using different modeling approaches that can handle both high- and low-resolution data, or a multi-scenario approach could be adopted to simulate different potential future trajectories, thus enriching the analysis and making it more comprehensive.

Additional Suggestions:
3. International context of agricultural intensification

Considering the global nature of agricultural intensification, it would be beneficial to position your findings within the broader international context. How do the trends observed in China compare to other countries that have pursued sustainable agricultural intensification? Can China learn from global experiences, or does it offer unique insights that could benefit other regions? A brief comparison with international trends could enhance the relevance of your findings and highlight the broader applicability of your study.

4. Emphasizing the innovation and key findings of the study

The manuscript would benefit from a clearer articulation of its unique contribution to the field. What makes this study innovative? How does it advance the current understanding of sustainable intensification, particularly in the Chinese context? It would be helpful to explicitly outline the key innovations of your study in the conclusion, ensuring that the most significant findings are clearly communicated to the reader.

5. Addressing the challenges of sustainable intensification

In the final paragraph of the results section, you mention the challenges of sustainable agricultural intensification in China. However, there is little explanation of how your study's findings can help address these challenges. While the study demonstrates the current state of agricultural intensification, it would be useful to discuss how your findings can inform potential solutions to these challenges, such as land degradation or the need for policy reforms. By offering suggestions for practical applications, your work could provide a clearer pathway toward addressing these critical issues.

Reviewer #2 (Remarks to the Author):

The authors have carefully addressed all of my previous concerns, and the revised manuscript has been substantially improved. The responses are clear and convincing, and the revisions have resolved the issues I raised. I believe the manuscript is now suitable for publication in its current form.

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Decision Letter:

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Dear Professor Liu,

Your manuscript titled "Cropland concentration powers sustainable intensification of agriculture in China" has now been seen by our reviewers, whose comments appear below. In light of their advice we are delighted to say that we are happy, in principle, to publish a suitably revised version in Communications Earth & Environment, provided that you can make proper statements based on your data, as raised by the reviewer.

We therefore invite you to revise your paper one last time to address the remaining concerns of our reviewers. At the same time we ask that you edit your manuscript to comply with our format requirements and to maximise the accessibility and therefore the impact of your work.

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We hope to hear from you within two weeks; please let us know if you need more time.

Best regards,

Mengjie Wang

Associate Editor, Communications Earth & Environment
Consulting Editor, Communications Sustainability
Bluesky: @commsearth.nature.com; @commssustain.nature.com

REVIEWERS' COMMENTS:

Reviewer #1 (Remarks to the Author):

The authors have addressed my previous concerns well. However, I have a few remaining minor points:
1. Line 262: Please rethink or further elaborate on the statement attributing crop yield increases to the extensive use of fertilizers and machinery. It is currently unclear how the provided data or analysis leads directly to this conclusion.
2. To improve transparency, please include a table summarizing the correlation between cropland landscape configuration and agricultural input intensity. This table should explicitly report the sample size, the specific model type used, p-values, and R2 coefficients.
3. Line 360: Please carefully re-verify Reference 53. This citation might not directly support the statement. Furthermore, please re-examine how the authors of that study determined and defined "farm size".

Response on both reviewers' comments:

Reviewer #1:

General comment: The manuscript offers an interesting analysis of cropland distribution and agricultural intensification trends in China over the past two decades, using a dataset compiled from Google Earth Engine and Landsat imagery. The study's findings on cropland concentration and its role in sustainable intensification provide valuable insights into China's agricultural future. However, there are several areas that require major revision for the paper to meet the standards of a high-quality publication.

Reply: We are very grateful for your constructive suggestions and believe that the comments help us to strongly improve the manuscript's quality. Below you will find our statements and clarifications to each comment.

Comment 01: The introduction is somewhat repetitive and could benefit from a more concise and focused presentation. Key concepts are introduced, but the central aim of the study and its innovative contribution are not immediately clear. The section could be streamlined to emphasize the specific knowledge gap that the study addresses—namely, how cropland concentration contributes to sustainable agricultural intensification in China.

Reply: Thank you very much for your comment. In the revised manuscript, we have re-emphasized the central knowledge gap of our study—namely, that the role of cropland concentration in promoting sustainable agricultural intensification in China remains a hypothesis rather than a validated conclusion. To clarify this point, we have explicitly included the following viewpoint in the introduction. Please check **Lines 106-109** in the revised manuscript.

Lines 106-109: "In addition, although cropland concentration is widely considered an effective strategy to promote sustainable intensification[17], there is still a lack of systematic evidence and broad consensus regarding its actual impact in the Chinese context."

To enhance clarity and logical flow, we have reorganized the introduction into the following structure:

i. Global food security challenges and agricultural intensification;
ii. Environmental concerns related to intensification;
iii. China's specific situation (e.g., excessive chemical use, fragmented farmland);
iv. Limitations of current evaluation methods and the need for remote sensing;
v. Research gap and contributions of this study.

This revised structure provides a more focused narrative and leads logically to our study's objectives and innovation. Please check **Lines 62-120** in the revised manuscript.

Lines 62-120: "Food security is a fundamental guarantee for human survival and development[3]. Despite a doubling of global crop production over the past half-century, global food security still faces severe challenges[4]. By the middle of this century, the global population is projected to reach 9 billion, with crop demand increasing by 100–110%[5]. To address this trend, agricultural intensification, which aims to enhance the productivity of existing cropland, has been widely recognized as a key strategy to alleviate pressure on food security.

However, traditional agricultural intensification primarily focuses on maximizing yield, often relying on the extensive use of fertilizers, mechanization, and pesticides[6]. While such practices can boost crop production, they also pose serious environmental threats, including non-point source pollution, greenhouse gas emissions, and soil degradation[7]. In China, approximately 30% of global fertilizer and pesticide consumption is concentrated[10]. Although this contributes to relatively high grain production, it has also led to the substantial loss of high-quality cropland[8].

China has long faced structural challenges such as land fragmentation, rural population aging, and rapid urban expansion[9,10]. Under the framework of the household responsibility system, combined with underdeveloped land transfer mechanisms, farmland has remained highly fragmented and small-scaled for decades[11,12]. Smallholder farmers are often associated with excessive use of agrochemicals, low labor efficiency, and uneven resource allocation[13], further constraining the improvement of agricultural intensification.

Against this backdrop, sustainable agricultural intensification has emerged as a key agenda for coordinating agricultural development and environmental protection. The early definition of sustainable intensification stated: "increase yield without expanding cropland area or causing adverse environmental effects[14]." In contrast to traditional intensification, the current approach emphasizes achieving higher yields with the same or fewer inputs while simultaneously ensuring food security and environmental sustainability[15,16]. Although genetically modified technologies offer the potential to increase yield without increasing environmental pressure, public resistance persists in some regions due to policy and ethical concerns[17,18]. Therefore, centralized cropland management, as a more practical and socially acceptable alternative, has gained increasing attention in both academic and policy circles[19]. Its potential lies in improving resource allocation efficiency and thereby enhancing yield per unit area[20].

The United Nations has incorporated indicators to assess sustainable agriculture into its Sustainable Development Goals (SDG), notably SDG 2.4.1[21]. Yet, such indicators primarily rely on household surveys, government statistics, and other ground-based data[22], limiting their applicability in large-scale and efficient assessments. In recent years, researchers have begun to explore the use of remote sensing technologies to evaluate the sustainability of agricultural intensification.

Although multiple global or regional land cover products have been developed[23-25] (e.g., GLC500m, MCD12Q1, GlobeLand30), these products focus on general land cover classification rather than the identification of actively cultivated cropland, resulting in cropland classification accuracy varying between 60–80%[26,27]. Moreover, most existing studies focus on static time points, lacking large-scale and long-term dynamic evaluations of sustainable agricultural intensification in China[28]. In addition, although cropland concentration is widely considered an effective strategy to promote sustainable intensification[19], there is still a lack of systematic evidence and broad consensus regarding its actual impact in the Chinese context.

We developed a systematic evaluation framework for sustainable agricultural intensification in China. Based on the conceptual foundation of sustainable intensification, we integrated remote sensing and machine learning techniques to extract actively cultivated cropland data at 30-meter resolution for five representative years from 2000 to 2020. Spatial changes in cropland patterns are assessed using three landscape metrics, including mean patch area (MPA), patch density (PD), and aggregation index (AI)[29]. In parallel, we incorporate national statistical data on fertilizer input, machinery power, irrigation water use, and crop yield to evaluate the sustainability of agricultural intensification. Finally, we compare cropland pattern data with farm size data to assess China's potential for large-scale cropland management and the future development of sustainable intensification."

Comment 02: The manuscript relies on data from only five years (2000, 2005, 2010, 2015, 2020), yet the authors discuss a 20-year analysis period. This choice raises questions regarding the sufficiency of the data, as the representation of trends may be limited by the gap between these data points. The authors should clarify why these specific years were chosen over continuous or more frequent sampling, and whether this selection affects the robustness of the study's conclusions. Additionally, the use of the term "5-phase" to describe the analysis could be misleading, as it implies continuous data rather than discrete time points. A clearer explanation of this terminology is needed.

Reply: Thank you for your valuable comment regarding the temporal resolution and terminology used in our study.

Regarding the selection of data:

At the early stage of this study, we attempted to include more years of data to improve temporal granularity. However, due to China's vast geographical expanse and climatic variability—especially in southern and mountainous areas—cloud-free or near-cloud-free Landsat imagery was limited in many years.

To enhance data quality and classification stability, we adopted a three-year composite strategy, combining images from the year before, the target year, and the year after each target year.

We have added a clarification regarding this strategy in the revised manuscript. Please check **Lines 416-419** in the revised manuscript.

Lines 416-419: "A three-year image set, including the target year, the year before, and the year after, was selected for each target year to represent cropland conditions and address limited data availability in some regions."

Regarding the data uncertainty:

We fully agree that using discrete time points may impose certain limitations on trend detection. We have added a discussion on the potential uncertainties and their implications for result robustness in the revised manuscript. Please check **Lines 453-458** in the revised manuscript.

Lines 453-458: "To reduce these uncertainties and enhance data consistency, we selected five discrete target years (2000, 2005, 2010, 2015, and 2020) and adopted a three-year composite strategy centered on each target year. While this approach improves classification accuracy and cross-year comparability, it may fail to capture abrupt changes in cropland patterns caused by natural disasters, extreme weather events, or intensive regional development."

Regarding the term "Five-Phase":

We appreciate the reviewer's suggestion regarding the term "five-phase." Our intention was to refer to five discrete target years, not a continuous time series. We have now revised all instances of "five-phase" to "five years" or "From 2000 to 2020", and removed the connecting lines in **Fig. 1c** to better reflect the nature of the data. Please check **Lines 38-40, Lines 123-125, Lines 133-135, Lines 145-147 and Lines 350-352** in the revised manuscript.

Lines 38-40: "Here, we map five years (2000, 2005, 2010, 2015, and 2020) cropland distribution using Google Earth Engine platform and 234,804 Landsat images and calculate representative landscape indexes."

Lines 123-125: “The overall accuracy of data extraction from the five years is above 93% (Supplementary Table 1; 93.78% for 2000, 95.18% for 2005, 95.53% for 2010, 94.04% for 2015, and 95.18% for 2020, respectively).”

Lines 133-135: “Spatial-temporal distribution characteristics of cropland was analyzed (Supplementary Fig. 1). The average cropland area over these five years was 178.23±5.56 Mha, representing 18.57% of China's land area.”

Lines 145-147: “Cropland area at 2015 is the lowest with only 169.26 Mha. Therefore, the year 2015 is considered as the turning point and the study period was divided into two phases: the contraction period (2000-2015) and the recovery period (2015-2020) (Fig. 1c).”

Lines 350-352: “From 2000 to 2020, proportions of croplands larger than 16 ha show an increase and are all greater than 85% of the China's total (Supplementary Fig. 3).”

Fig. 1c in the revised manuscript:

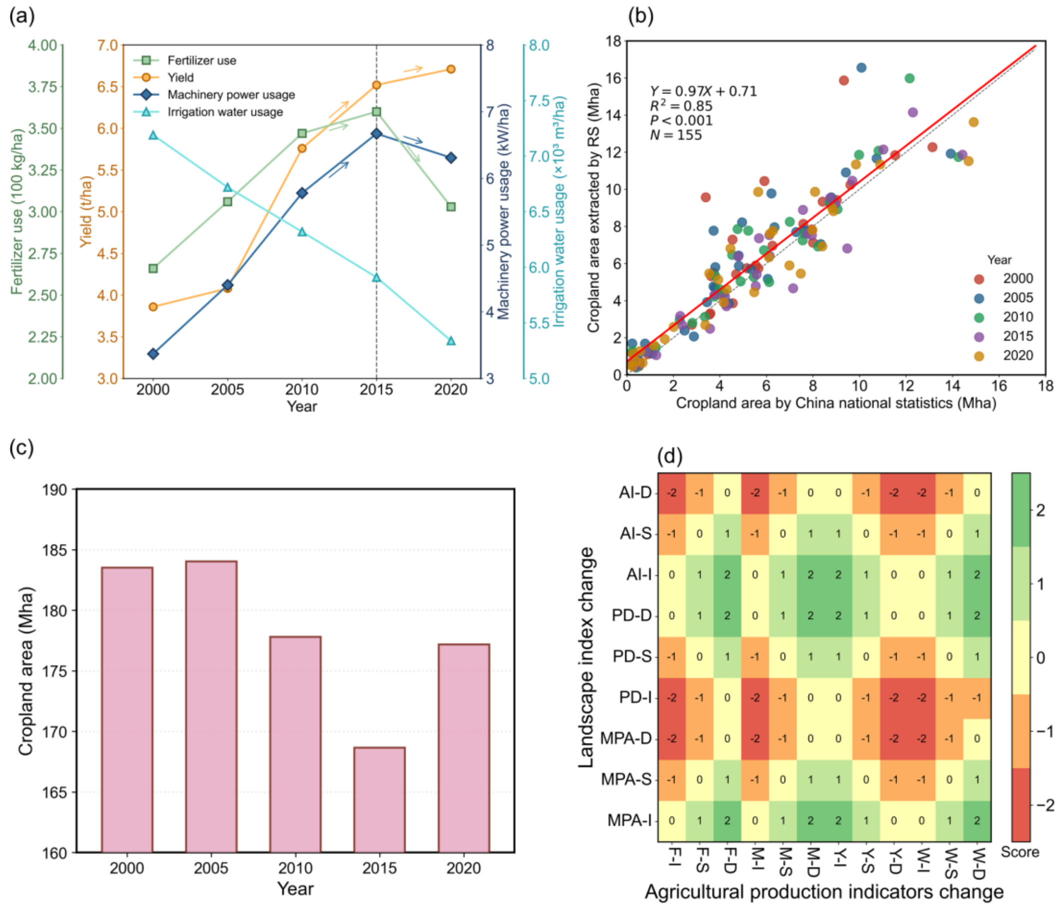


Fig. 1| Evaluation method and extraction results. a, Changes in agricultural production indicators from 2000 to 2020. **b**, Comparison of extracted cropland area with cropland area from national statistics data. **c,** Changes in cropland area from 2000 to 2020**. d,** Evaluation matrix of change patterns on the contribution to sustainable agricultural intensification.

Comment 03: The statement regarding the sharing of advanced agricultural technologies with low-yielding countries (lines 77-79) seems tangential to the core focus of the paper. It does not directly support the study's main argument about cropland concentration and sustainable intensification in China.

Reply: Thank you for your insightful comment.

Our original intent was not to emphasize international technology transfer, but rather to point out that certain technological innovations, such as genetically modified technologies, can help reduce agricultural inputs per unit yield while maintaining or increasing productivity. However, due to policy constraints and limited social acceptance, these technologies often face significant challenges in promotion and practical application.

We revised the relevant paragraph in the introduction to clarify this point. Compared with biotechnological solutions such as genetic modification, centralized cropland management is presented as a more feasible and widely applicable strategy to support sustainable agricultural intensification in the Chinese context. Please check **Lines 90-95** in the revised manuscript.

Lines 90-95: "Although genetically modified technologies offer the potential to increase yield without increasing environmental pressure, public resistance persists in some regions due to policy and ethical concerns[17,18]. Therefore, centralized cropland management, as a more practical and socially acceptable alternative, has gained increasing attention in both academic and policy circles[19]. Its potential lies in improving resource allocation efficiency and thereby enhancing yield per unit area[20]."

References:

15 Tilman, D. *et al.* Global food demand and the sustainable intensification of agriculture. *Proc. Natl. Acad. Sci. U. S. A.* **108**, 20260-20264 (2011).

16 Smith, P. Delivering food security without increasing pressure on land Pete Smith. *Glob Food Secur-Agr* **2**, 18-23 (2013).

17 Zhang, B. B. *et al.* A company-dominated pattern of land consolidation to solve land fragmentation problem and its effectiveness evaluation: A case study in a hilly region of Guangxi Autonomous Region, Southwest China. *Land Use Policy* **88** (2019).

18 Deng, O. P. *et al.* Managing fragmented croplands for environmental and economic benefits in China. *Nat. Food* **5** (2024).

Comment 04: In the "Potential and challenges for sustainable intensification of agriculture in China" session, the authors briefly mention government reforms related to agricultural water use, but this aspect is not discussed in the body of the paper. Given the critical role of irrigation in agricultural intensification, it would be beneficial to incorporate irrigation as an additional input factor in the analysis. The authors could explore its role in shaping agricultural sustainability alongside the changes in fertilizer and machinery inputs. Including this factor would enhance the depth and comprehensiveness of the study.

Reply: Thank you for your valuable comment. In our previous version, irrigation water use was only included in the supplementary materials rather than in the core evaluation matrix. We have now incorporated it as a potential factor influencing agricultural intensification, revised the evaluation criteria and classification scheme accordingly, and updated the relevant results and discussion sections involving irrigation water use. This includes the updated **Fig. 1a, Fig. 3** and **Fig. 4** in the revised manuscript, **Supplementary Table 2**, **Supplementary Table 3**, and **Supplementary Table 9** in the revised supplementary materials.

Moreover, we made substantial enhancements to the analytical framework to better uncover the relationship between cropland concentration and sustainable agricultural intensification in China. Specifically, we added a new section titled "Development of agricultural input intensity indicators" in the Methods, where we established a coupling analysis framework linking cropland landscape patterns with agricultural input efficiency—serving as a supplement and reinforcement of the original method.

Using data from 31 provincial-level administrative regions across the country, we developed three agricultural input intensity indicators (fertilizer use, machinery power, and irrigation water use), normalized by unit crop yield to reflect the level of agricultural resource consumption under comparable output conditions.

By pairing provinces and years, we coupled landscape pattern metrics—mean patch area (MPA), aggregation index (AI), and patch density (PD)—with the input intensity indicators, and conducted separate trend regressions for the contraction period (2000–2015) and the recovery period (2015–2020). This allowed us to examine whether a higher degree of cropland concentration (e.g., larger MPA or higher AI) is associated with reduced resource consumption per unit yield. We have incorporated the above content into the **Methods** section. Please check **Lines 578-622** in the revised manuscript.

Through this approach, we obtained results that more strongly support the central argument of our manuscript. These findings have been added to the main Results section (please check **Lines 303-330** in the revised manuscript), along with a new figure (**Fig. 5**) and a supplementary figure (**Supplementary Fig. 2**).

Lines 578-622:

"Development of agricultural input intensity indicators

To analyze the period-specific differences in agricultural resource use associated with changes in cropland landscape configuration, this study used 31 provincial administrative units across China as analytical units. Three agricultural input intensity indicators—fertilizer, mechanization, and irrigation—were developed to represent the use levels of major agricultural resources under comparable unit yield conditions. In parallel, three landscape pattern indices, including MPA, AI and PD were extracted to characterize the spatial configuration of cropland across provinces. Based on the division of a contraction period (2000–2015) and a recovery period (2015–2020), province-year paired samples were established by matching each province's landscape configuration with corresponding resource input intensities. Linear regression model were applied to examine the association and changing patterns between cropland landscape structure and agricultural resource use across different periods, to determine whether improvements in landscape configuration are accompanied by enhanced resource use efficiency in agriculture.

The definitions and calculation methods of the three input intensity indicators are described as follows:

(1) Fertilizer Intensity

Fertilizer Intensity measures the amount of fertilizer applied per unit of grain yield. It is defined as the ratio between fertilizer application and crop yield per hectare, with units of tons per ton (t/t):"

$$\text{Fertilizer Intensity} = \frac{\text{Fertilizer (t/ha)}}{\text{Yield (t/ha)}} \tag{1-2}$$

where *Fertilizer* represents the fertilizer applied per hectare (t/ha), and *Yield* refers to grain yield per hectare (t/ha). The ratio thus reflects the quantity of fertilizer required to produce one ton of grain.

(2) Mechanization Intensity

Mechanization Intensity reflects the agricultural machinery power required per unit of output. It is calculated as the ratio between total machinery power per hectare and crop yield, with units of kilowatts per ton (kW/t):

$$\text{Mechanization Intensity} = \frac{\text{Machinery power usage (kW/ha)}}{\text{Yield (t/ha)}} \tag{1-3}$$

where *Machinery power usage* is the total agricultural machinery capacity per hectare (kW/ha), and *Yield* is the grain output per hectare.

(3) Irrigation Intensity

Irrigation Intensity measures the amount of irrigation water used per ton of crop yield. It is defined as the ratio between irrigation water input and yield per hectare, with units of cubic meters per ton (m^3/t):

$$\text{Irrigation Intensity} = \frac{\text{Irrigation Water } (m^3/ha)}{\text{Yield } (t/ha)} \tag{1-4}$$

where *Irrigation Water* represents the total volume of irrigation water applied per hectare (m^3/ha), and Yield is the grain output per hectare.

All three indicators are output-based resource consumption metrics, reflecting the agricultural system's reliance on key inputs. Higher values indicate greater input consumption per unit of output and, consequently, higher resource dependency. Lower values suggest more efficient or conservative resource use.

Combined with the temporal evolution of cropland landscape metrics, these indicators provide a quantitative basis for assessing whether cropland consolidation contributes to improved resource use efficiency. Their integration helps to elucidate the role of landscape configuration in facilitating the transition toward more sustainable and intensive agricultural systems.

Lines 303-330： "To further verify whether cropland concentration contributes to improved resource use efficiency, we conducted a correlation analysis between cropland landscape configuration indices and agricultural input intensity indicators across 31 provincial-level administrative units (**Fig. 5, Supplementary Fig. 2**). By comparing paired provincial samples between the contraction period (2000–2015) and the recovery period (2015–2020), we observed notable temporal differences in the relationship between landscape patterns and agricultural inputs. Specifically, during the contraction period, larger patch sizes and higher aggregation levels were positively correlated with greater fertilizer and mechanization input intensity, indicating that cropland concentration at that stage did not lead to enhanced resource use efficiency (in fact, widespread cropland fragmentation was observed during this period). In contrast, this relationship reversed during the recovery period—provinces with more concentrated cropland exhibited lower fertilizer and mechanization intensity per unit yield, suggesting that improvements in landscape configuration were accompanied by enhanced agricultural input efficiency.

In comparison, irrigation input intensity showed a relatively stable negative correlation with cropland concentration in both periods, indicating that improvements in irrigation efficiency were likely driven more by water-saving policies and technological progress rather than changes in spatial cropland configuration. These findings further demonstrate that during the recovery period, cropland consolidation significantly contributed to reducing reliance on fertilizers and agricultural machinery, thereby improving input efficiency.

In conclusion, advancing sustainable agricultural intensification in China can be achieved through promoting cropland connectivity, expanding cropland size, improving resource use efficiency, and minimizing agricultural chemical pollution. Meanwhile, the Chinese government has also identified large-scale cropland operation as a central strategy for promoting sustainable intensification, which is expected to effectively alleviate farmland abandonment caused by population aging and labor shortages[11]."

We also **updated the relevant sections** following the inclusion of the irrigation water indicator, including changes in the descriptions, interpretations, and the grade of sustainable agricultural intensification. Please check **Lines 188-190, Line 299-300, Lines 551-557, Lines 565-571 and Line 629** in the revised manuscript.

Lines 188-190: "In terms of agricultural inputs, this study respectively analyzed fertilizer use, agricultural machinery power, and irrigation water use (Fig. 1a)."

Line 299-300: "Particularly, 16 regions were graded as Grade A, including one region classified as Grade A+."

Lines 551-557: "F-I, M-I, W-I and Y-D patterns, deemed as "negative", represent increased dependency on fertilizer use, machinery power, and irrigation water, along with a decline in crop yield. These patterns indicate higher environmental pressure and unsustainable agricultural intensification. In contrast, F-D, M-D, W-D and Y-I patterns are considered "positive", as they indicate reduced dependence on fertilizer, machinery, and irrigation water, along with improved crop yield, thereby reflecting lower environmental pressure and a trend toward sustainable agricultural intensification."

Lines 565-571: "Firstly, we scored each change pattern according to their degree of change. We assigned a score of -1 for change patterns that have negative impact on cropland change and the environment (i.e., MPA-D, PD-I, AI-D, F-I, M-I, W-I and Y-D). A score of 0 was assigned for change patterns that basically have no impact (i.e., MPA-S, PD-S, AI-S, F-S, M-S, W-S and Y-S). We assigned a score of +1 for change patterns that have positive impact on cropland change and the environment (i.e., MPA-I, PD-D, AI-I, F-D, M-D, W-D and Y-I)."

Line 629: "...six grades (i.e., A+, A, B, C, D, E, F). Grade A+ and A denotes..."

Some relevant conclusions were added. Please check **Lines 210-213, Line 264-267 and Line 273-276** in the revised manuscript.

Line 210-213: "In contrast, driven by policy interventions, irrigation water use per unit area in China has continuously declined over the past two decades, indicating reduced irrigation input and improved water use efficiency, thereby promoting sustainable agricultural intensification."

Line 264-267: "During this period, although only three regions experienced an increase in irrigation water use per unit area (W-I), most regions still exhibited increasing cropland fragmentation, suggesting that improvements in irrigation water efficiency alone had a limited effect on promoting sustainable agricultural intensification."

Line 273-276: "Meanwhile, irrigation water use efficiency continued to improve, with irrigation water use per unit area showing a sustained decline, further reinforcing the dual trend of reducing agricultural input intensity and improving resource use efficiency."

Fig. 1a in the revised manuscript:

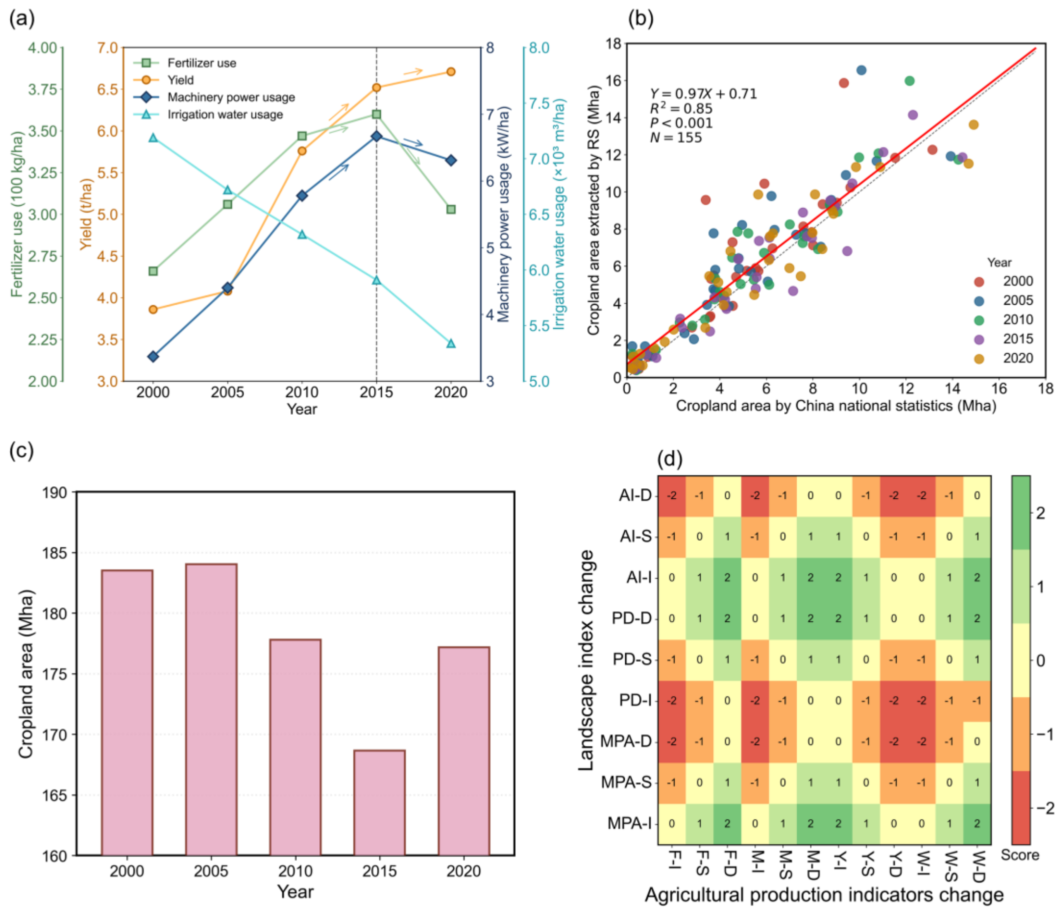


Fig. 1| Evaluation method and extraction results. a, Changes in agricultural production indicators from 2000 to 2020. **b**, Comparison of extracted cropland area with cropland area from national statistics data. **c,** Changes in cropland area from 2000 to 2020**. d,** Evaluation matrix of change patterns on the contribution to sustainable agricultural intensification.

Fig. 3 in the revised manuscript:

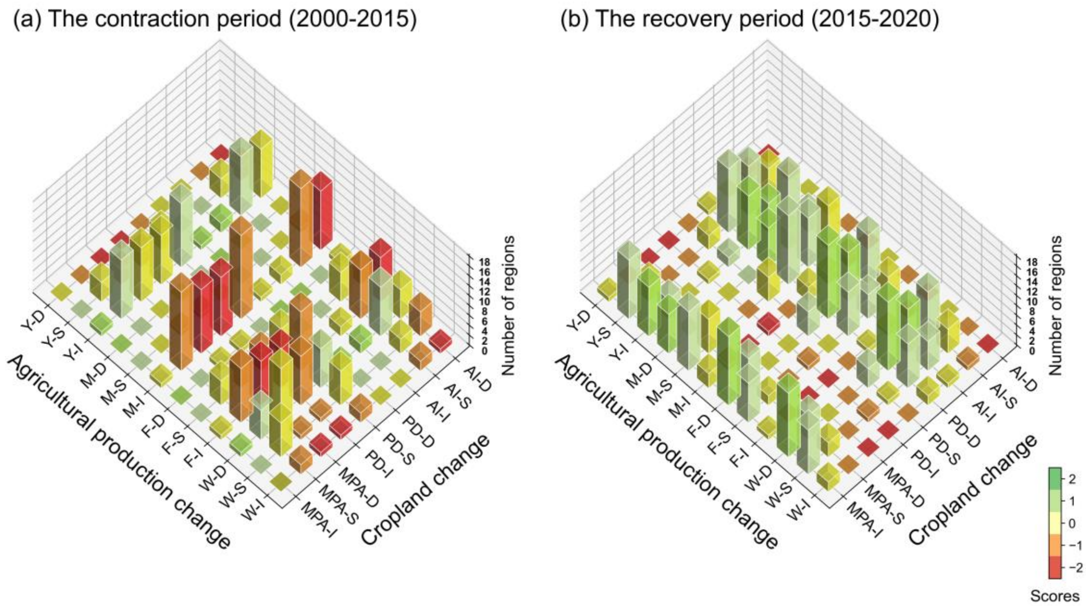


Fig. 3| Number of regions for each combination of change patterns. a, the contraction period from 2000 to 2015. **b**, the recovery period from 2015 to 2020. **Note:** The X and Y axes respectively reflect the change patterns of landscape indexes and agricultural production indicators, which together determine the pattern combination of a region. The height of the Z axis represents the number of regions under each combination. Color mapping is used to represent the contribution level of these combinations to sustainable agricultural intensification.

Fig. 4 in the revised manuscript:

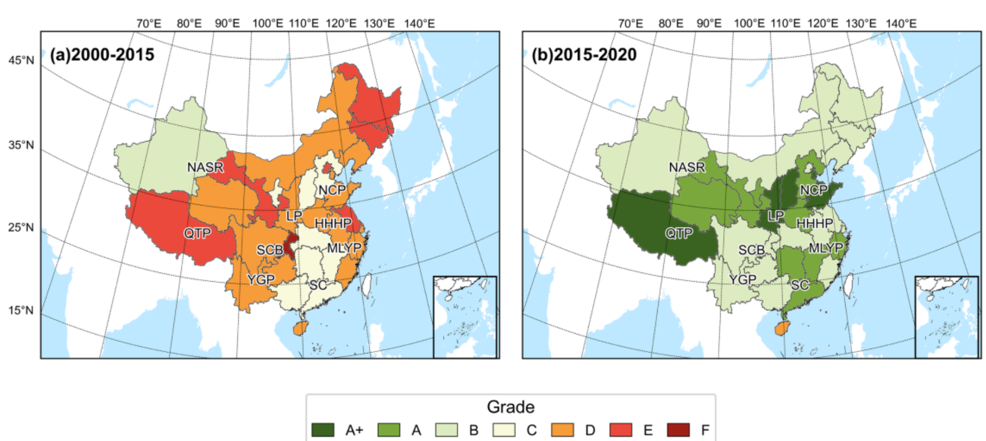


Fig. 4| The degree of sustainable intensification of agriculture in provincial administrative regions. **a**, The contraction period from 2000 to 2015. **b**, In the recovery period from 2015 to 2020.

Fig. 5 in the revised manuscript:

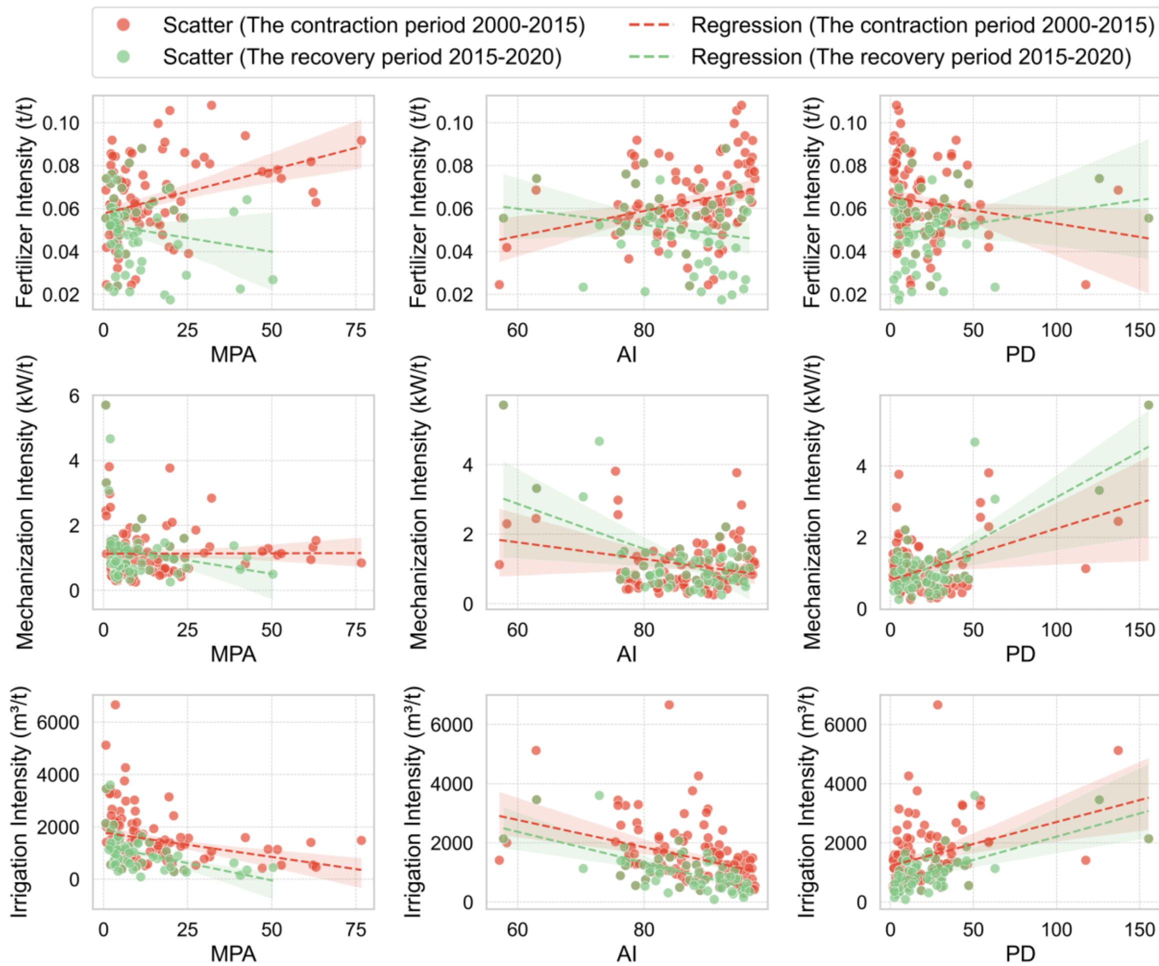
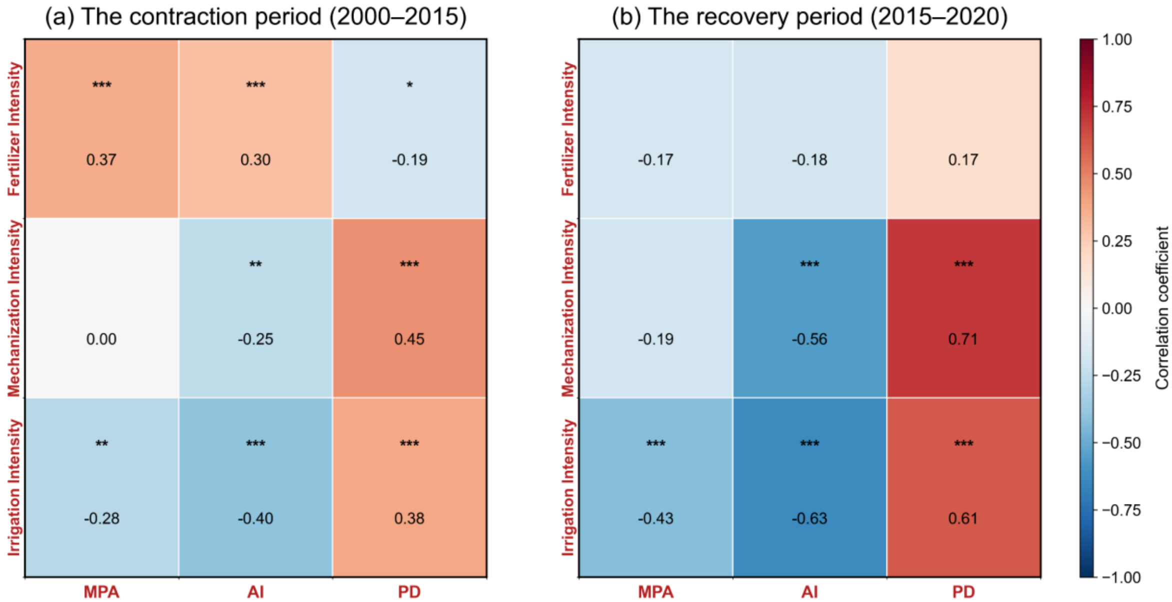


Fig. 5| The degree of sustainable intensification of agriculture in provincial administrative regions.

Supplementary Fig. 2:



Supplementary Fig. 2 | Correlation between cropland landscape configuration and agricultural input intensity across periods. Pearson correlation heatmaps between landscape pattern indices (MPA, AI, PD) and agricultural input intensity indicators (fertilizer, mechanization, and irrigation intensity). (a) Contraction period (2000–2015); (b) Recovery period (2015–2020). The correlation analysis is based on provincial-level data across 31 regions in mainland China. Asterisks indicate significance levels (*p < 0.05, **p < 0.01, ***p < 0.001).

Supplementary Table 2 | Summary of the number of regions with different patterns of cropland and agricultural production indicators changes in each period.

Stage	Agricultural Production Indicators	Change Pattern	MPA			PD			AI		
			I	S	D	I	S	D	I	S	D
Contraction period	F	I	1	11	9	8	12	1	2	10	9
		S	0	5	4	4	5	0	0	6	3
		D	0	0	1	1	0	0	0	0	1
	M	I	1	16	13	12	17	1	2	16	12
		S	0	0	1	1	0	0	0	0	1
		D	0	0	0	0	0	0	0	0	0
	Y	I	1	12	11	10	13	1	2	12	10
		S	0	4	3	3	4	0	0	4	3
		D	0	0	0	0	0	0	0	0	0
	W	I	0	2	1	1	2	0	0	2	1
		S	0	7	1	1	7	0	0	3	5
		D	1	6	11	10	8	1	2	10	6
Recovery period	F	I	1	0	0	0	0	1	1	0	0
		S	8	2	0	1	0	9	5	5	0
		D	14	6	0	0	5	15	10	10	0
	M	I	3	1	0	1	0	3	2	2	0
		S	12	7	0	0	5	14	10	9	0
		D	8	0	0	0	0	8	4	4	0
	Y	I	10	4	0	1	2	11	6	8	0
		S	12	4	0	0	3	13	10	6	0
		D	1	0	0	0	0	1	0	1	0
	W	I	2	0	0	0	0	2	1	1	0
		S	9	3	0	1	1	9	6	5	0
		D	13	5	0	0	4	14	9	9	0

Supplementary Table 3 | Change patterns and sustainability intensification ratings for 31 provincial-level administrative regions after including irrigation water use in the agricultural production indicators.

Agricultural production zone	Provincial administrative region	2000-2015							Score	Grade	2015-2020							Score	Grade
		MPA	PD	AI	F	M	Y	W			MPA	PD	AI	F	M	Y	W		
NCP	Heilongjiang	D	I	D	I	I	I	D	-3	E	S	S	I	D	S	S	S	2	B
	Jilin	D	I	D	I	I	I	D	-3	E	I	D	S	D	S	S	S	3	B
	Liaoning	D	I	S	S	I	I	D	-1	D	S	S	S	D	S	I	D	3	B
NASR	Inner Mongolia	D	I	S	I	I	I	D	-2	D	S	S	S	D	S	I	D	3	B
	Xinjiang	I	D	I	I	I	I	D	3	B	I	D	S	S	S	S	D	3	B
	Gansu	D	I	D	S	I	I	S	-3	E	I	D	I	S	S	I	D	5	A
	Ningxia	S	S	I	I	I	I	D	1	C	I	D	I	S	D	S	D	5	A
HHHP	Beijing	D	I	D	I	I	I	D	-3	E	I	D	S	S	I	S	D	2	B
	Tianjin	D	I	D	I	S	I	D	-2	D	I	D	S	D	D	I	D	6	A+
	Hebei	S	S	S	I	I	I	D	0	C	I	D	S	D	D	S	S	4	A
	Shandong	D	I	S	S	I	I	D	-1	D	I	D	S	D	D	I	D	6	A+
	Henan	D	I	S	I	I	I	D	-2	D	I	D	S	D	D	D	D	4	A
LP	Shaanxi	S	S	S	I	I	I	S	-1	D	I	D	I	D	S	I	D	6	A+
	Shanxi	S	S	S	I	I	I	D	0	C	I	D	I	S	D	I	D	6	A+
QTP	Qinghai	S	S	S	S	I	S	I	-2	D	I	D	I	D	S	S	D	5	A
	Tibet	D	I	S	I	I	S	D	-3	E	I	D	I	D	D	S	D	6	A+
MLYP	Anhui	D	S	S	I	I	I	D	-1	D	I	D	S	D	S	S	S	3	B
	Jiangsu	D	I	D	S	I	I	I	-4	E	I	D	S	D	S	I	I	3	B
	Jiangxi	S	S	S	S	I	I	S	0	C	I	D	I	D	S	S	D	5	A
	Zhejiang	S	S	D	I	I	I	S	-2	D	I	D	I	D	D	S	S	5	A
	Hunan	S	S	S	S	I	S	D	0	C	I	D	I	S	I	I	D	4	A
	Shanghai	D	I	D	D	I	S	D	-2	D	I	D	I	S	S	S	S	3	B
	Hubei	S	S	D	I	I	I	S	-2	D	I	D	I	D	S	S	I	3	B

Agricultural production zone	Provincial administrative region	2000-2015							Score	Grade	2015-2020							Score	Grade
		MPA	PD	AI	F	M	Y	W			MPA	PD	AI	F	M	Y	W		
SCB	Sichuan	S	S	S	S	I	S	I	-2	D	S	D	I	D	S	S	S	3	B
	Chongqing	D	I	D	I	I	S	S	-5	F	S	D	S	S	S	I	D	3	B
YGP	Yunnan	S	S	D	I	I	I	D	-1	D	S	S	I	D	S	S	D	3	B
	Guizhou	S	S	D	S	I	S	S	-2	D	S	S	S	D	S	S	D	2	B
	Guangxi	S	S	S	I	I	I	D	0	C	I	D	S	S	S	I	S	3	B
SC	Guangdong	S	S	S	I	I	I	D	0	C	I	D	I	D	S	I	S	5	A
	Fujian	S	S	D	I	I	I	S	-2	D	I	D	I	I	I	I	S	2	B
	Hainan	S	S	S	I	I	I	S	-1	D	S	I	S	S	I	I	S	-1	D

Note: 'I' represents an increase in the change pattern, 'S' represents a stable change pattern, 'D' represents a decrease in the change pattern, 'W' represents irrigation water .

Supplementary Table 9 | Division of change patterns.

Period	Change pattern	Landscape indexes and agricultural production indicators						
		AI	PD	MPA	F	M	Y	W
Contraction period	I	>1.44	>27.17	>18.41	>0.69	>0.57	>1.07	>0.12
	S	-1.44~1.44	-27.17~27.17	-18.41~18.41	-0.69~0.69	-0.57~0.57	-1.07~1.07	-0.12~0.12
	D	<-1.44	<-27.17	<-18.41	<-0.69	<-0.57	<-1.07	<-0.12
Recovery period	I	>3.18	>16.13	>58.02	>0.30	>0.97	>0.42	0.07
	S	-3.18~3.18	-16.13~16.13	-58.02~58.02	-0.30~0.30	-0.97~0.97	-0.42~0.42	-0.07~0.07
	D	<-3.18	<-16.13	<-58.02	<-0.30	<-0.97	<-0.42	<-0.07

Notes: The numbers in the table represent the threshold "H". AI: Aggregation Index; PD: Patch Density; MPA: Mean Patch Area; F: Fertilizer use; M: Total machinery power usage; Y: Crop yield; W: Irrigation water; I: Increase; S: Stable; D: Decrease

Reference:

11 Ren, C. C. *et al.* The impact of farm size on agricultural sustainability. *J. Clean. Prod.* **220**, 357-367 (2019).

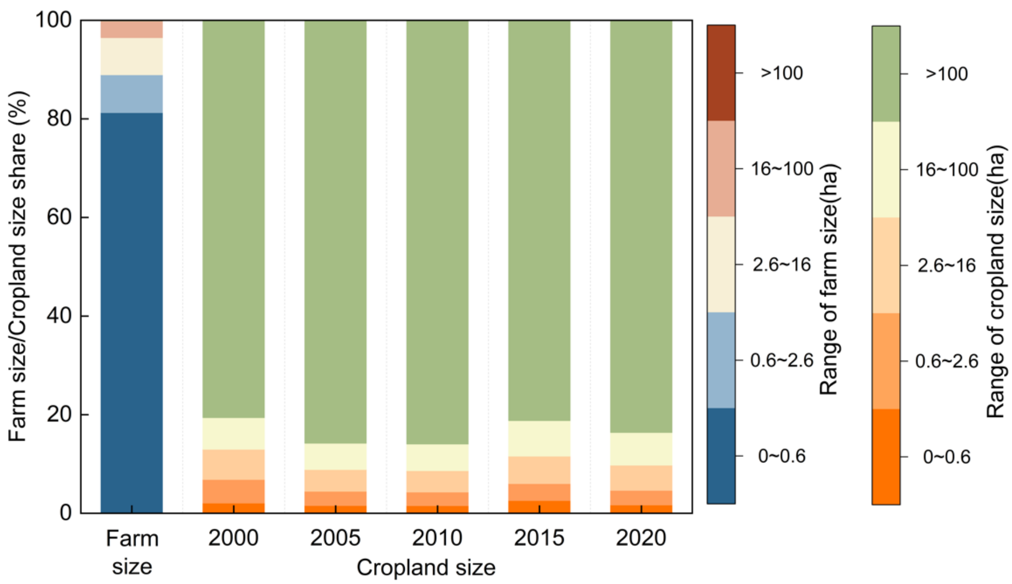
44 National Agricultural Water Conservation Development Program (2001–2010). *State Development Planning Commission of the People's Republic of China* (2001).

45 National Program for Agricultural Water Conservation (2012–2020). *General Office of the State Council of the People's Republic of China* (2012).

Comment 05: Figure 5 presents data without significant analysis or interpretation and feels more suited for the appendix rather than the main body of the manuscript. The figure does not provide substantial explanatory value in its current form and should either be reworked to provide more analytical insights or moved to the supplementary material to avoid detracting from the narrative.

Reply: Thank you for your suggestion. In response, we have moved the figure to the supplementary materials as **Supplementary Fig. 3** to maintain the focus and coherence of the main text.

Supplementary Fig. 2:



Supplementary Fig. 3 | Proportion of farm size and cropland size in each range. The data of farm size were derived from Lesiv et al.35. "Farm size" is the area of cropland that has already achieved scale operation "cropland size" refers to the area of contiguous cropland patches.

Comment 06: This paper focus on historical and current trends but do not explore potential future trajectories of cropland concentration and its effects on sustainable intensification. The inclusion of projections or simulations that model the potential long-term impacts of cropland concentration would make the study more forward-looking and robust. This would strengthen the paper's argument for the sustainability of agricultural intensification under the current trajectory of cropland concentration.

Reply: Thank you for your insightful comment. We fully agree that incorporating future projections could provide a more forward-looking perspective. But we encountered the following problems during the test experiment:

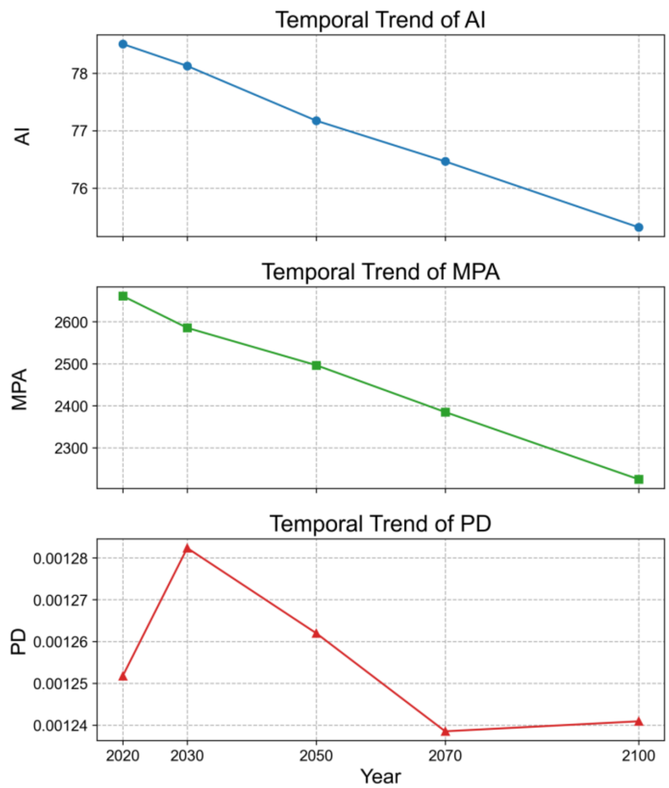
Large spatial resolution mismatch between available projection datasets and our historical data. Most widely used land use simulation datasets—such as the LUH2-GLOBAL-SSP-RCP scenarios9 (Zhang, T., Cheng, C. & Wu, X. Mapping the spatial heterogeneity of global land use and land cover from 2020 to 2100 at a 1 km resolution. Scientific Data 10, 748 (2023))—have a coarse spatial resolution of 1 km. In contrast, our study uses cropland data at a finer 30 m resolution. This resolution mismatch significantly affects the calculation of landscape pattern metrics, such as patch density (PD), edge density (ED), and mean patch area (MPA). For example, we tested LUH2 1-km simulation data and found that at this coarse scale, core landscape indicators such as the Aggregation Index (AI) and MPA show declining trends, which contradict our empirical findings (**Fig. A**).

As noted in **Lines 347-350** of the manuscript: "The data of farm size revealed that over 80% of the cropland belongs to small-scale farms (<0.6 ha), and large-scale farms (>16 ha) only account for 10% (**Supplementary Fig. 3**). This predominance of small-scale farms in China is primarily due to the Household Responsibility System[10]."

Such small plot changes are difficult to capture at a 1 km^2 resolution, thus introducing uncertainty and potential bias into simulations.

Therefore, incorporating such simulation datasets directly into this study would pose practical challenges. However, we fully recognize the value of long-term forecasting and plan to explore reliable approaches in future research to simulate cropland dynamics and assess their implications for sustainable agricultural intensification.

Fig. A:



References:

10 Tan, S. *et al.* Land fragmentation and its driving forces in China. *Land Use Policy* **23**, 272-285 (2006).

Comment 07: While the dataset used in the study is extensive, the selection of only five years leaves room for concern about the representativeness and robustness of the findings. The authors should address whether this limited temporal coverage might overlook short-term fluctuations or fail to capture more granular trends. A more detailed explanation of the rationale for this data selection, including any potential limitations, would improve the paper's transparency and reliability.

Reply: We appreciate the reviewer's suggestion regarding the term "five-phase." Our intention was to refer to five discrete target years, not a continuous time series. We have now revised all instances of "five-phase" to "five years" or "From 2000 to 2020", and removed the connecting lines in **Fig. 1c** to better reflect the nature of the data. Please check **Lines 38-40, Lines 123-125, Lines 133-135 and Lines 350-352** in the revised manuscript.

Lines 38-40: "Here, we map five years (2000, 2005, 2010, 2015, and 2020) cropland distribution using Google Earth Engine platform and 234,804 Landsat images and calculate representative landscape indexes."

Lines 123-125: "The overall accuracy of data extraction from the five years is above 93% (Supplementary Table 1; 93.78% for 2000, 95.18% for 2005, 95.53% for 2010, 94.04% for 2015, and 95.18% for 2020, respectively)."

Lines 133-135: "Spatial-temporal distribution characteristics of cropland was analyzed (Supplementary Fig. 1). The average cropland area over these five years was 178.23±5.56 Mha, representing 18.57% of China's land area."

Lines 350-352: "From 2000 to 2020, proportions of croplands larger than 16 ha show an increase and are all greater than 85% of the China's total (Supplementary Fig. 3)."

Acknowledgment and Discussion of Data Uncertainty

We also fully acknowledge that using discrete time points may impose certain limitations on trend detection. We have added a discussion on the potential uncertainties and their implications for result robustness in the revised manuscript. Please check **Lines 453-458** in the revised manuscript.

Lines 453-458: "To reduce these uncertainties and enhance data consistency, we selected five discrete target years (2000, 2005, 2010, 2015, and 2020) and adopted a three-year composite strategy centered on each target year. While this approach improves classification accuracy and cross-year comparability, it may fail to capture abrupt changes in cropland patterns caused by natural disasters, extreme weather events, or intensive regional development."

Comment 08: The term "agricultural intensification" is frequently used but would benefit from a more explicit definition. It is not clear whether the term refers exclusively to technological inputs, crop yields, or other socio-economic factors. A clearer definition would help readers understand the scope of the study and the specific aspects of intensification that are being analyzed.

Reply: Thank you for your insightful comment. We have carefully revised the manuscript to clarify both the conceptual and methodological elements you pointed out.

In response to your suggestion, we revised the Introduction to clearly distinguish between traditional agricultural intensification and sustainable agricultural intensification. Please check **Lines 69-72** and **line 85-89** in the revised manuscript.

Lines 69-72: "However, traditional agricultural intensification primarily focuses on maximizing yield, often relying on the extensive use of fertilizers, mechanization, and pesticides[4]. While such practices can boost crop production, they also pose serious environmental threats, including non-point source pollution, greenhouse gas emissions, and soil degradation[5]."

Lines 84-89: "The early definition of sustainable intensification stated: "increase yield without expanding cropland area or causing adverse environmental effects[12]". In contrast to traditional intensification, the current approach emphasizes achieving higher yields with the same or fewer inputs while simultaneously ensuring food security and environmental sustainability[13,14]."

References:

4 Pei, H. W. *et al.* Impacts of varying agricultural intensification on crop yield and groundwater resources: comparison of the North China Plain and US High Plains. *Environ. Res. Lett.* **10** (2015).

5 Sun, B. *et al.* Agricultural non-point source pollution in China: causes and mitigation measures. *Ambio* **41**, 370-379 (2012).

12 Baulcombe, D. *et al. Reaping the benefits: science and the sustainable intensification of global agriculture*. (The Royal Society, 2009).

13 Barnes, A. P. & Thomson, S. G. Measuring progress towards sustainable intensification: How far can secondary data go? *Ecol. Indic.* **36**, 213-220 (2014).

14 Dillon, E. J. *et al.* Measuring progress in agricultural sustainability to support policy-making. *Int. J. Agric. Sustain.* **14**, 31-44 (2016).

***Comment 09*:** The article lacks an analysis of the uncertainty in the input data and how this uncertainty propagates in the calculations. Given the complexity of agricultural systems and potential measurement errors, assessing how these uncertainties affect the results is crucial. A detailed uncertainty analysis would help quantify potential variations in the results, providing a clearer understanding of the reliability and robustness of the conclusions. Without such analysis, the findings might be interpreted too confidently, especially when applied to policy or agricultural planning.

Reply: Thank you for your insightful comment. We have carefully revised the manuscript to clarify both the conceptual and methodological elements you pointed out.

In response to your suggestion, we revised the Introduction to clearly distinguish between traditional agricultural intensification and sustainable agricultural intensification. Please check **Lines 69-72** and **line 84-89** in the revised manuscript.

Lines 69-72: "However, traditional agricultural intensification primarily focuses on maximizing yield, often relying on the extensive use of fertilizers, mechanization, and pesticides[4]. While such practices can boost crop production, they also pose serious environmental threats, including non-point source pollution, greenhouse gas emissions, and soil degradation[5]."

Lines 84-89: "The early definition of sustainable intensification stated: "increase yield without expanding cropland area or causing adverse environmental effects[12]". In contrast to traditional intensification, the current approach emphasizes achieving higher yields with the same or fewer inputs while simultaneously ensuring food security and environmental sustainability[13,14]."

We also clarified the rationale for using the Freedman–Diaconis rule in our analysis. The following explanation was added to the Methods section, Please check **Lines 539-543** in the revised manuscript.

Lines 539-543: "The Freedman–Diaconis rule was originally developed for probability density estimation and histogram binning. In this study, it was not used to directly model the temporal dynamics of agricultural or landscape indicators, but rather served as a statistical basis for dividing indicator change intervals, in order to enhance the objectivity and robustness of the binning criteria."

Reference:

4 Pei, H. W. *et al.* Impacts of varying agricultural intensification on crop yield and groundwater resources: comparison of the North China Plain and US High Plains. *Environ. Res. Lett.* **10** (2015).

5 Sun, B. *et al.* Agricultural non-point source pollution in China: causes and mitigation measures. *Ambio* **41**, 370-379 (2012).

12 Baulcombe, D. *et al. Reaping the benefits: science and the sustainable intensification of global agriculture*. (The Royal Society, 2009).

13 Barnes, A. P. & Thomson, S. G. Measuring progress towards sustainable intensification: How far can secondary data go? *Ecol. Indic.* **36**, 213-220 (2014).

14 Dillon, E. J. *et al.* Measuring progress in agricultural sustainability to support policy-making. *Int. J. Agric. Sustain.* **14**, 31-44 (2016).

Reviewer #2:

Comment 01: The study follows conventional workflows without introducing substantial methodological advancements. It primarily validates known patterns rather than proposing a new framework or addressing a critical gap in sustainable intensification research. The authors should consider whether the study could go beyond confirming expected trends to tackle an unresolved challenge in agricultural intensification.

Reply: Thank you for your insightful comment. In the revised manuscript, we have re-emphasized the central knowledge gap of our study—namely, that the role of cropland concentration in promoting sustainable agricultural intensification in China remains a hypothesis rather than a validated conclusion. To clarify this point, we have explicitly included the following viewpoint in the introduction Please check **Lines 106-109** in the revised manuscript.

Lines 106-109: "In addition, although cropland concentration is widely considered an effective strategy to promote sustainable intensification[17], there is still a lack of systematic evidence and broad consensus regarding its actual impact in the Chinese context." This underpins the novelty of our study, which provides the first national-scale empirical evaluation of this assumption, based on long-term remote sensing data and a multidimensional index system.

This underpins the novelty of our study, which provides the first national-scale empirical evaluation of this assumption, based on long-term remote sensing data and a multidimensional index system.

References:

17 Zhang, B. B. *et al.* A company-dominated pattern of land consolidation to solve land fragmentation problem and its effectiveness evaluation: A case study in a hilly region of Guangxi Autonomous Region, Southwest China. *Land Use Policy* **88** (2019).

Comment 02: The use of the Freedman-Diaconis rule for defining change patterns in landscape indices and agricultural production indicators raises concerns. This rule is traditionally used for histogram binning, and its application to classify agricultural change patterns—especially with spatial-temporal variations—needs further justification. How does it account for the temporal dynamics and spatial heterogeneity of agricultural change?

Reply: Thank you for your insightful comment. We have carefully revised the manuscript to clarify both the conceptual and methodological elements you pointed out.

In this study, the Freedman–Diaconis rule was not used to directly model the spatiotemporal dynamics of agricultural production changes. Rather, it served as a statistical basis for dividing indicator variation intervals, aiming to enhance the objectivity and stability of the binning results.

The landscape pattern indices (e.g., AI, PD, MPA) and agricultural production indicators (e.g., M, F, Y) analyzed in this study are all annual change metrics that were derived through prior processing and possess clear temporal resolution. The Freedman–Diaconis rule was used here to define thresholds for classifying "significant change" (I/D) versus "relative stability" (S).

More importantly, to better account for spatiotemporal heterogeneity, we did not apply a single uniform binning standard across all years. Instead, we determined separate threshold ranges for different periods (i.e., the Contraction period and Recovery period), as shown in Supplementary Table 10. This approach not only considers the stage-based characteristics of agricultural system evolution, but also reflects structural differences in data distributions across time periods, thereby ensuring the relative validity of the pattern classification.

We clarified the rationale for using the Freedman–Diaconis rule in our analysis. The following explanation was added to the Methods section, Please check **Lines 539-543** in the revised manuscript.

Lines 539-543: "The Freedman–Diaconis rule was originally developed for probability density estimation and histogram binning. In this study, it was not used to directly model the temporal dynamics of agricultural or landscape indicators, but rather served as a statistical basis for dividing indicator change intervals, in order to enhance the objectivity and robustness of the binning criteria."

Comment 03: The classification of agricultural regions is inconsistent. While the study initially divides China into nine agricultural production zones, Fig. 3 presents results at the provincial level. The rationale behind this discrepancy should be clarified.

Reply: Thank you very much for your comment. We consider that the use of both provincial administrative divisions and agricultural zoning is not contradictory but represents a complementary strategy from different spatial scales for analysis and visualization. The inclusion of agricultural zones is intended to provide a macro-level background of agricultural patterns and to help explain the spatial heterogeneity of agricultural development across regions. However, in the data processing and visualization stages, we primarily used provincial-level administrative units as the basic spatial analysis scale, based on the following considerations:

(1) Higher spatial resolution: Using provinces as the basic unit for analysis and visualization enables higher spatial resolution, allowing for a more detailed depiction of regional differences in the degree of cropland intensification.

(2) Greater policy relevance and applicability: Agricultural resource allocation and policy implementation in China are typically organized at the provincial level. Therefore, results at this scale are more practical for horizontal comparison and more aligned with future needs for regional policy development and management. In contrast, agricultural zoning is based more on natural geography and climate conditions and is better suited as a supplementary perspective for macro-level interpretation.

(3) Complementary information for visualization: To help readers better interpret **Fig. 3**, we added provincial administrative boundaries in **Fig. 4** to show the spatial patterns of agricultural intensification at a broader scale. The two spatial units complement each other in both analysis and visualization, facilitating multi-level understanding of regional differences in intensification levels.

Fig. 4 in the revised manuscript:

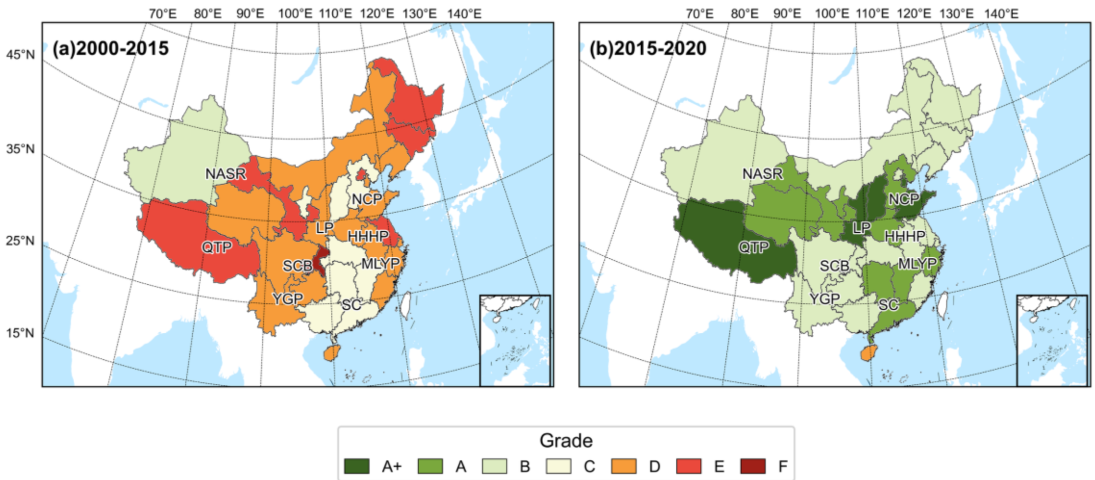


Fig. 4| The degree of sustainable intensification of agriculture in provincial administrative regions. **a**, The contraction period from 2000 to 2015. **b**, In the recovery period from 2015 to 2020.

Comment 04: The study generates cropland maps across five periods but does not justify why existing cropland datasets were not used. If the newly created maps offer higher classification accuracy, this advantage should be explicitly demonstrated rather than assumed based on similarity with previous results.

Reply: Thank you for your valuable comment. We have already provided relevant explanations in the original manuscript to describe why we developed a customized cropland dataset instead of using existing land use products. Please check **Lines 473-476** in the revised manuscript and **Lines 237-238** in the revised supplementary material.

Although a number of land cover datasets are available, most of them exhibit at least one of the following limitations:

(1) a general land use focus that fails to identify actively cultivated cropland[1,2];

(2) limited temporal coverage that does not meet our requirement for consistent data across five representative years from 2000 to 2020;

(3) inconsistent methodologies and cropland definitions compared with our study.

Specifically, many existing datasets define cropland broadly as land with agricultural potential, without considering whether it was actively cultivated during the sampling year. In contrast, our study defines cropland strictly as land planted with crops in each target year. For example, Zhai et al. (2024) adopted the same definition and their findings on cropland trends align well with ours[3], while Zhou et al. (2023) used a broader cropland definition, resulting in significantly different trends[4]. Therefore, to ensure consistency with our analytical goals and to support accurate landscape pattern assessments, we constructed a tailored cropland dataset.

Lines 473-476: "In our study, we took the lands that are being used for growing crops as cropland samples. Based on this viewer, visual inspection and manual selection of cropland and non-cropland pixels that remained relatively stable throughout the study period were performed."

Lines 237-238 in the revised supplementary material: "In our study, we took the lands that are being used for growing crops as cropland samples at the sampling period."

References:

3 Zhai, J. H. *et al.* Is the boom in staple crop production attributed to expanded cropland or improved yield? A comparative analysis between China and India. *Sci. Total Environ.* **933** (2024).

4 Zhou, Y. *et al.* Cultivated land loss and construction land expansion in China: Evidence from national land surveys in 1996, 2009 and 2019. *Land Use Policy* **125** (2023).

Additional Comment 01: The introduction provides a strong background on food security and agricultural intensification but could be better structured. A suggested logical flow:

i. Global food security challenges and agricultural intensification

ii. Environmental concerns related to intensification

iii. China's specific situation (e.g., excessive chemical use, fragmented farmland)

iv. Limitations of current evaluation methods and the need for remote sensing

v. Research gap and contributions of this study

Reply: Thank you for your suggestion. To enhance clarity and logical flow, we have reorganized the introduction into the following structure:
i. Global food security challenges and agricultural intensification;
ii. Environmental concerns related to intensification;
iii. China's specific situation (e.g., excessive chemical use, fragmented farmland);
iv. Limitations of current evaluation methods and the need for remote sensing;
v. Research gap and contributions of this study.

This revised structure provides a more focused narrative and leads logically to our study's objectives and innovation. Please check **Lines 62-120** in the revised manuscript.

Lines 62-120: "Food security is a fundamental guarantee for human survival and development[3]. Despite a doubling of global crop production over the past half-century, global food security still faces severe challenges[4]. By the middle of this century, the global population is projected to reach 9 billion, with crop demand increasing by 100–110%[5]. To address this trend, agricultural intensification, which aims to enhance the productivity of existing cropland, has been widely recognized as a key strategy to alleviate pressure on food security.

However, traditional agricultural intensification primarily focuses on maximizing yield, often relying on the extensive use of fertilizers, mechanization, and pesticides[6]. While such practices can boost crop production, they also pose serious environmental threats, including non-point source pollution, greenhouse gas emissions, and soil degradation[7]. In China, approximately 30% of global fertilizer and pesticide consumption is concentrated[10]. Although this contributes to relatively high grain production, it has also led to the substantial loss of high-quality cropland[8].

China has long faced structural challenges such as land fragmentation, rural population aging, and rapid urban expansion[9,10]. Under the framework of the household responsibility system, combined with underdeveloped land transfer mechanisms, farmland has remained highly fragmented and small-scaled for decades[11,12]. Smallholder farmers are often associated with excessive use of agrochemicals, low labor efficiency, and uneven resource allocation[13], further constraining the improvement of agricultural intensification.

Against this backdrop, sustainable agricultural intensification has emerged as a key agenda for coordinating agricultural development and environmental protection. The early definition of sustainable intensification stated: “increase yield without expanding cropland area or causing adverse environmental effects[14].” In contrast to traditional intensification, the current approach emphasizes achieving higher yields with the same or fewer inputs while simultaneously ensuring food security and environmental sustainability[15,16]. Although genetically modified technologies offer the potential to increase yield without increasing environmental pressure, public resistance persists in some regions due to policy and ethical concerns[17,18]. Therefore, centralized cropland management, as a more practical and socially acceptable alternative, has gained increasing attention in both academic and policy circles[19]. Its potential lies in improving resource allocation efficiency and thereby enhancing yield per unit area[20].

The United Nations has incorporated indicators to assess sustainable agriculture into its Sustainable Development Goals (SDG), notably SDG 2.4.1[21]. Yet, such indicators primarily rely on household surveys, government statistics, and other ground-based data[22], limiting their applicability in large-scale and efficient assessments. In recent years, researchers have begun to explore the use of remote sensing technologies to evaluate the sustainability of agricultural intensification.

Although multiple global or regional land cover products have been developed[23-25] (e.g., GLC500m, MCD12Q1, GlobeLand30), these products focus on general land cover classification rather than the identification of actively cultivated cropland, resulting in cropland classification accuracy varying between 60–80%[26,27]. Moreover, most existing studies focus on static time points, lacking large-scale and long-term dynamic evaluations of sustainable agricultural intensification in China[28]. In addition, although cropland concentration is widely considered an effective strategy to promote sustainable intensification[19], there is still a lack of systematic evidence and broad consensus regarding its actual impact in the Chinese context.

We developed a systematic evaluation framework for sustainable agricultural intensification in China. Based on the conceptual foundation of sustainable intensification, we integrated remote sensing and machine learning techniques to extract actively cultivated cropland data at 30-meter resolution for five representative years from 2000 to 2020. Spatial changes in cropland patterns are assessed using three landscape metrics, including mean patch area (MPA), patch density (PD), and aggregation index (AI)[29]. In parallel, we incorporate national statistical data on fertilizer input, machinery power, irrigation water use, and crop yield to evaluate the sustainability of agricultural intensification. Finally, we compare cropland pattern data with farm size data to assess China's potential for large-scale cropland management and the future development of sustainable intensification."

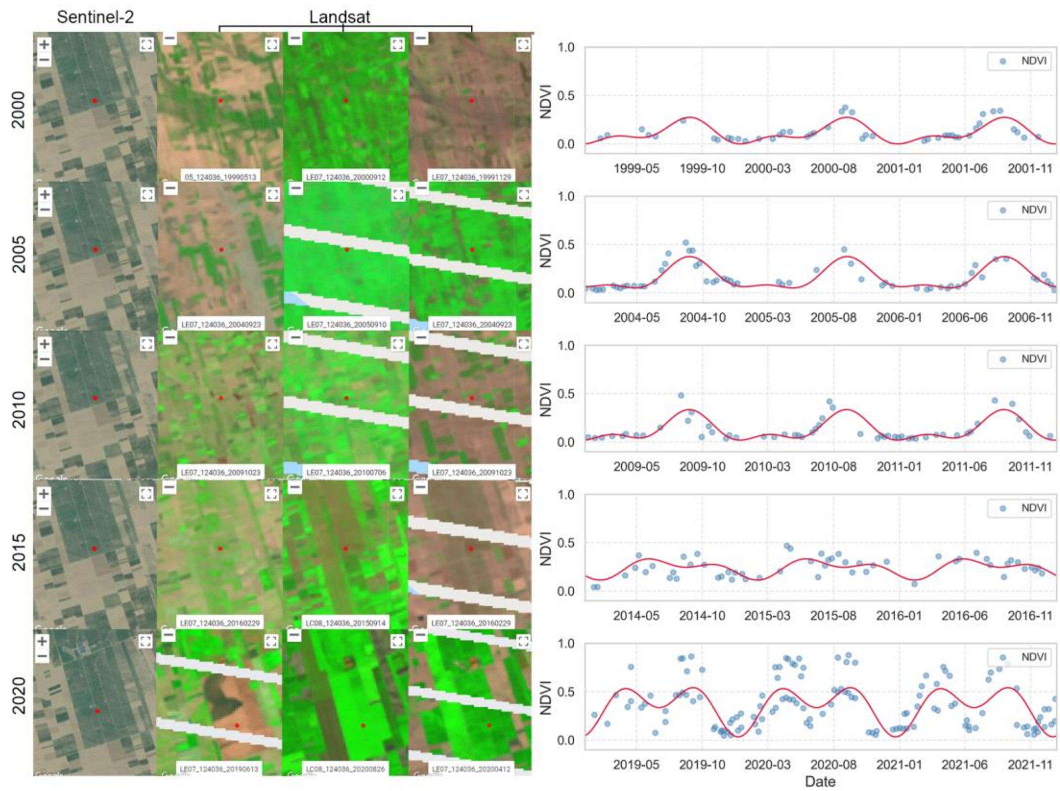
Additional Comment 02: Abbreviations: Once an acronym is introduced, the full term should not be repeated.

Reply: Thank you for your suggestion. As required by the journal, we placed the Methods section at the end of the manuscript. Therefore, all abbreviations are defined upon their first appearance in the Methods, and we use abbreviations consistently throughout the main text wherever possible.

Additional Comment 03: Supplementary Fig. 4 appears to be a direct screenshot from GEE's console, which seems unpolished. A more refined presentation is recommended.

Reply: Thank you for your suggestion. We have revised the figure, particularly by enhancing the sharpness of the points, lines, and text on the right side. Please check

Supplementary Fig. 6 in the revised manuscript.



Supplementary Fig. 6 | Sample selection time series viewing tool. This figure shows stable cropland in the location (113.15°E, 34.87°N) for each period. Each row presents high-resolution Google Earth imagery and Landsat imagery (R, G, B: 7, 5, 4), where the Landsat images are selected from within a one-year range centered around the target year. The selected sample is marked with a red dot. Below the Google Earth and Landsat imagery, time series of NDVI, BSI, Tasseled Cap Brightness, Greenness, and Wetness of the calibration sample are plotted. L4_7_SR stands for Landsat 4-7 surface reflectance, L8_SR indicates Landsat 8 surface reflectance, and S2_TOA refers to the top-of-atmosphere reflectance of Sentinel 2a and 2b. In our study, we took the lands that are being used for growing crops as cropland samples at the sampling period.

Additional Comment 04: Figs. 1 & 4: High-saturation colors should be avoided for clarity.

> **Reply:** Thank you for your helpful suggestion. We have modified the color scheme in the revised Fig. 3 to reduce saturation and improve clarity. Corresponding adjustments have also been made to Fig. 1d.

Fig. 1a in the revised manuscript:

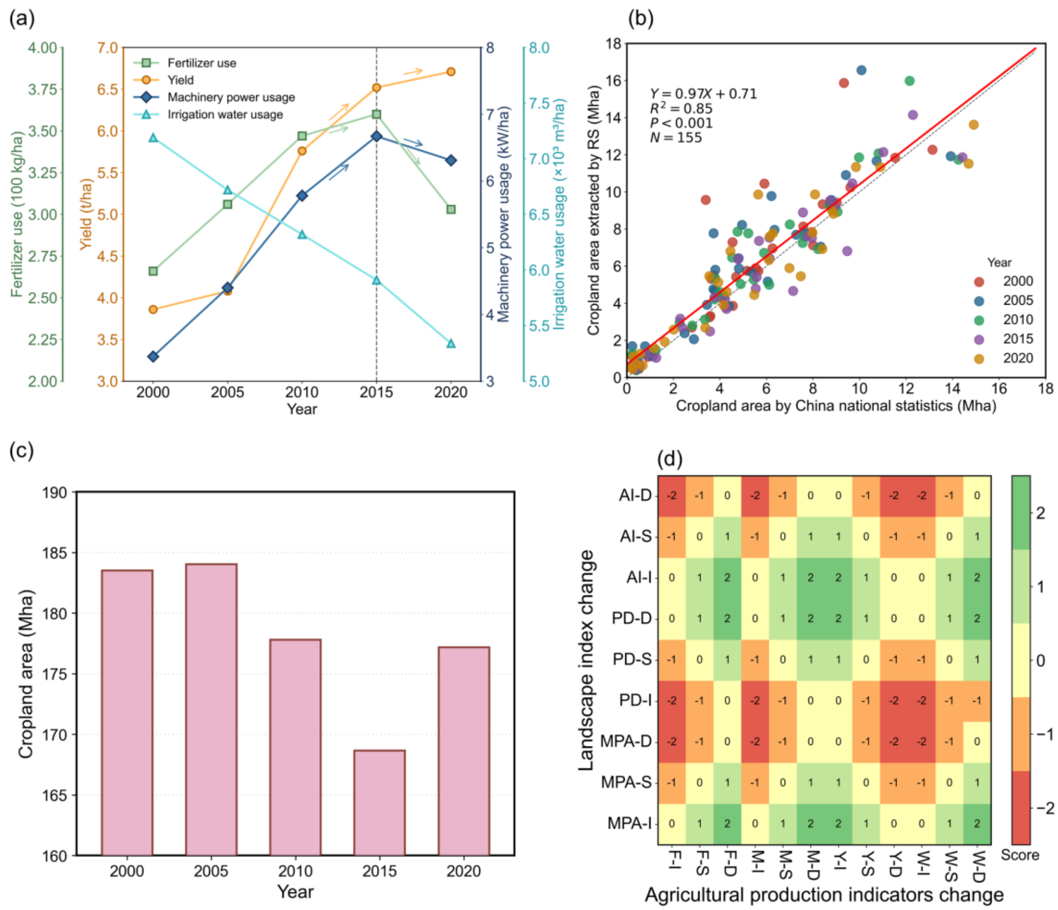


Fig. 1| Evaluation method and extraction results. a, Changes in agricultural production indicators from 2000 to 2020. **b**, Comparison of extracted cropland area with cropland area from national statistics data. **c,** Changes in cropland area from 2000 to 2020**. d,** Evaluation matrix of change patterns on the contribution to sustainable agricultural intensification.

Fig. 3 in the revised manuscript:

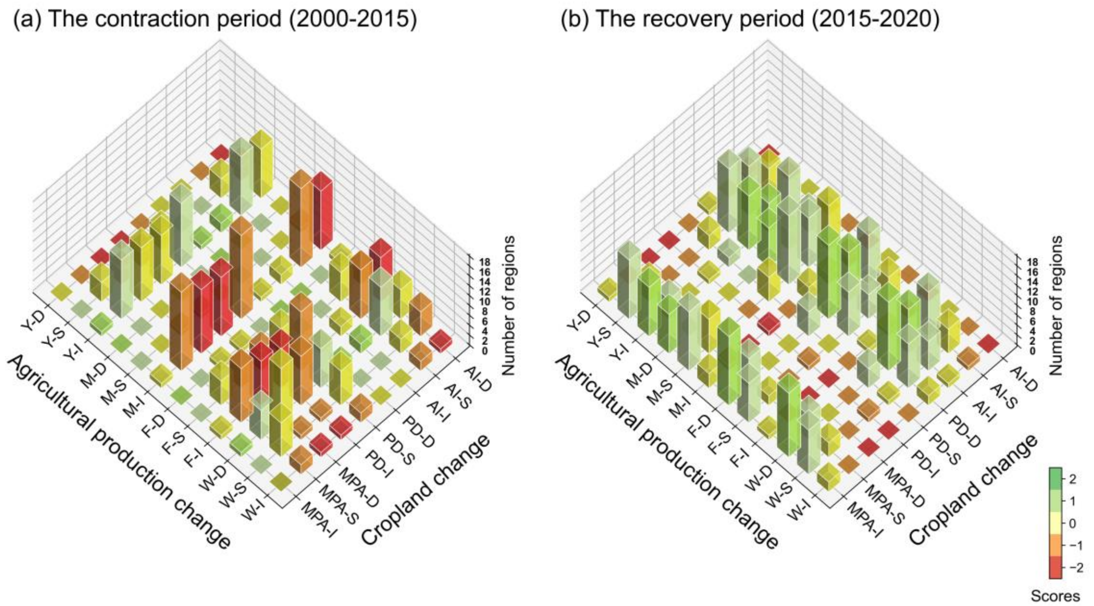


Fig. 3| Number of regions for each combination of change patterns. a, the contraction period from 2000 to 2015. **b**, the recovery period from 2015 to 2020. **Note:** The X and Y axes respectively reflect the change patterns of landscape indexes and agricultural production indicators, which together determine the pattern combination of a region. The height of the Z axis represents the number of regions under each combination. Color mapping is used to represent the contribution level of these combinations to sustainable agricultural intensification.

Response on both reviewers' comments:

Reviewer #1:

General comment: Thank you for the revisions and the additional clarifications you provided in your response. I have reviewed the manuscript again, and I would like to offer feedback on two critical aspects that were raised previously but have not been fully addressed. While your paper offers valuable insights into agricultural intensification, there are several areas that require further refinement to strengthen the robustness and relevance of the study.

> **Reply:** Thank you for your valuable comments. Your suggestions have significantly improved the rigor and completeness of our study. In the revised manuscript, we have carefully addressed the two key issues you raised and also provided additional responses to the other three supplementary concerns.

Comment 01: Uncertainty analysis of input data

In the earlier round of review, it was emphasized that an analysis of the uncertainty in the input data and its propagation through the calculations is essential. This is particularly important in agricultural systems, where measurement errors and model assumptions can significantly influence the study's conclusions.

Although your response acknowledged this concern, the revised manuscript does not provide a detailed uncertainty analysis. The current version presents the results without clearly quantifying how uncertainties in the data, such as spatial resolution mismatches or measurement errors, might impact the conclusions. A thorough uncertainty analysis would be instrumental in assessing the reliability and robustness of your findings, offering a more nuanced interpretation.

> **Reply:** Thank you very much for your comment. In the revised manuscript, we conducted a quantitative analysis of potential uncertainties in the input data—for example, we assessed whether the use of different cropland datasets will influence the conclusions. Please check **Lines 505-508** in the revised manuscript and **Supplementary Note 8, Supplementary Fig.8** in the revised Supplementary material.
>
> **Lines 505-508:** "A quantitative uncertainty analysis was performed to evaluate both the potential errors in the input data and their propagation through the computational workflow, providing insights into how these variations may affect the reliability and robustness of the study's conclusions (Supplementary Note 8; Supplementary Fig. 8)."
>
> **Supplementary Note 8：**Input Uncertainty Propagation Analysis
>
> To assess the impact and propagation effects of input data discrepancies on the calculation of landscape pattern metrics, we conducted an uncertainty propagation

analysis. This analysis aimed to quantify the response of landscape metric results to variations in input data, thereby evaluating the robustness and reliability of the outcomes.

(1) Input Discrepancy Assessment

The analysis was conducted using data from 31 provincial-level administrative units across China (excluding Hong Kong, Macao, and Taiwan) at five time points: 2000, 2005, 2010, 2015, and 2020. Based on the comparison between the cropland dataset generated in this study (Mine dataset) and the CLCD dataset[13], we calculated the relative difference in cropland area for each province to characterize the inconsistency between input datasets. The input difference (X) was defined as:

$$X = \frac{|A_{Mine} - A_{CLCD}|}{A_{Mine}} \times 100\% \qquad (8\text{-}1)$$

where A_{Mine} and A_{CLCD} represent the cropland areas (km²) from the Mine and CLCD datasets, respectively, and X denotes the relative deviation (%) between the two input datasets.

(2) Result Difference Quantification

Landscape pattern metrics including Mean Patch Area (MPA), Patch Density (PD), and Aggregation Index (AI) were calculated based on the two input datasets. The result difference was quantified as follows:

$$Y_i = \frac{\left|I_{i,\,Mine} - I_{i,\,CLCD}\right|}{I_{i,\,Mine}} \times 100\% \qquad (8\text{-}2)$$

where I_i represents the value of the i-th landscape metric. Y_i denotes the percentage difference in results. In total, 155 paired samples were obtained for each landscape metric.

(3) Model Fitting

To characterize the propagation relationship between input difference (X) and result difference (Y), we employed a logarithmic regression model. Given that both input and result differences are strictly positive percentage variables and exhibit right-skewed distributions, logarithmic transformation was applied to reduce the influence of extreme values and linearize their proportional relationship. The model is expressed as:

$$log(Y_i + \varepsilon) = \alpha_i + \beta_i X + \epsilon \qquad (8\text{-}3)$$

Exponentiating both sides yields:

$$Y_i = e^{\alpha} \cdot e^{\beta X_i} \quad (8\text{-}4)$$

where Y_i denotes the result difference (%) of the i-th landscape metric (MPA, PD, or AI), X represents the input cropland area difference (%), ε is a small constant to avoid taking the logarithm of zero, ϵ is the random error term, e denotes Euler's number, the base of the natural logarithm, and β_i is the sensitivity coefficient.

(4) Output Relative Change Rate

To facilitate the interpretation of the physical meaning of the sensitivity coefficient β_i, we further define the relative change rate of the output metric R_i as:

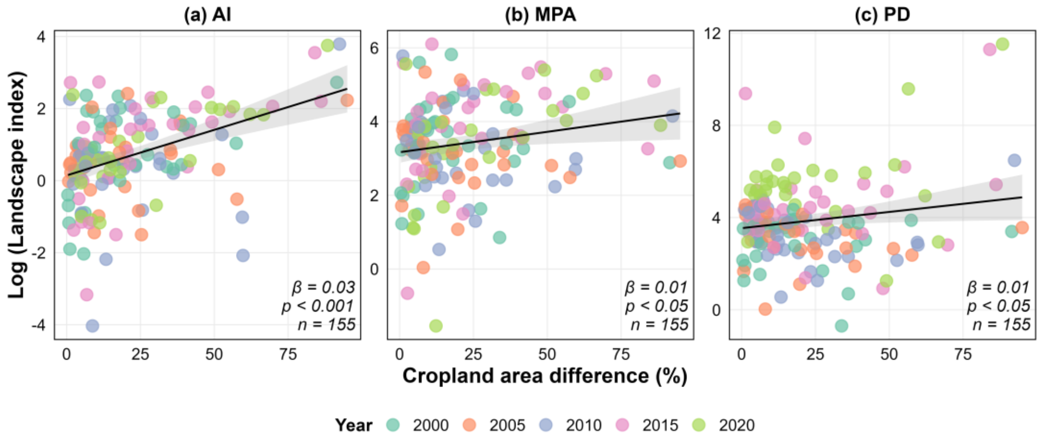
$$R_i = e^{\beta_i \Delta X} - 1 \quad (8\text{-}5)$$

where R_i represents the relative change rate of the i-th landscape metric, β_i is the sensitivity coefficient, and ΔX denotes the increase in input difference (%). This equation quantifies the proportional change in the output metric when the input difference increases by ΔX percentage points.

(5) Regression Results and Interpretation

The regression analysis revealed the extent of error propagation from input data discrepancies to landscape metric outcomes. Interpreting the β coefficient as a measure of propagation magnitude, a 1% increase in input cropland area difference results in an average change of approximately 2.56% in the aggregation index (AI), indicating a relatively stronger transmission effect. In contrast, the corresponding changes in mean patch area (MPA) and patch density (PD) are approximately 1.12% and 1.42%, respectively. These results suggest that although input data discrepancies do propagate to metric outcomes, the overall magnitude of such effects is modest and does not compromise the robustness of the main conclusions. (Supplementary Fig.8).

Supplementary Fig.8



Supplementary Fig. 8 | Relationships between provincial cropland area difference and three log-transformed landscape indexes from 2000 to 2020. (a) aggregation index (AI), (b) largest patch index (MPA), and (c) patch density (PD). Points show yearly observations. The black line indicates the linear regression fit, and the gray shading shows the 95% confidence interval. β, p, and n represent the regression slope, statistical significance, and sample size, respectively.

References:

13 Yang, J. & Huang, X. The 30 m annual land cover dataset and its dynamics in China from 1990 to 2019. *Earth Syst. Sci. Data* **13**, 3907-3925 (2021).

Comment 02: Future projections and trajectories of cropland concentration

While your manuscript focuses on historical trends and current data, incorporating future projections or simulations that model the long-term impacts of cropland concentration is an essential aspect that has not been fully addressed. Including projections would not only make the study more forward-looking but also provide valuable insights into the sustainability of agricultural intensification under future scenarios.

You raised valid concerns regarding the mismatch in spatial resolution between the historical data (30m resolution) and the future simulation datasets (1 km resolution). However, the response did not explore sufficiently alternative methods or techniques to address this issue. For example, simulations could be conducted using different modeling approaches that can handle both high- and low-resolution data, or a multi-scenario approach could be adopted to simulate different potential future trajectories, thus enriching the analysis and making it more comprehensive.

Reply: Thank you for highlighting the importance of incorporating future projections to better understand the long-term implications of cropland intensification. In the revised manuscript, we now explicitly address this point by adding a baseline scenario of China's cropland pattern to 2040.

To avoid the resolution mismatch between our historical 30-m dataset and the commonly used 1-km land-use projections, we developed a spatially explicit Markov–cellular automata framework at a consistent 30-m resolution, drawing on recent advances in patch-based land-use simulation models (e.g., PLUS and FLUS). Using the calibrated model, we projected cropland distribution to 2040 under a business-as-usual scenario and recalculated provincial-level landscape indexes (mean patch area, patch density and aggregation index) to characterize the future trajectories of cropland structure.

The results show that future changes are dominated by stability rather than major reorganization: in most provinces, cropland landscapes remain within the "stable" category in terms of patch size, fragmentation and aggregation. Some eastern and central provinces exhibit a trend toward larger and more aggregated cropland patches, while parts of northeastern China show slightly increased fragmentation. These findings suggest that, under the current trajectory, cropland intensification in China is more likely to occur through incremental structural adjustment and local consolidation rather than large-scale spatial redistribution.

To keep the main text focused, we summarized these key findings (please check **lines 425–429** in the revised manuscript), while detailed technical settings and full experimental results are provided in the Supplementary Materials (**Supplementary Note 7,**

Supplementary Table 10–Supplementary Table 14, Supplementary Fig. 9–Supplementary Fig. 12).

Lines 425-429: "The results of the 2040 baseline simulation indicate that provincial cropland configurations remain largely stable, with only slight changes in patch size, fragmentation, and aggregation. Future cropland changes may be dominated by stability rather than dramatic reorganization, and China's cropland landscapes are more likely to undergo gradual structural adjustment (Supplementary Note 7)."

Supplementary Note 7：Cropland Simulation Framework and Future Scenario Analysis

To provide a forward-looking assessment of China's cropland system, we used the calibrated Markov–CA framework to simulate the 2040 baseline scenario at a 30 m resolution. This projection offers insights into the likely direction and magnitude of future structural adjustments in cropland patterns, revealing the potential persistence or reorganization of landscape characteristics. Detailed modeling settings and supplementary results are documented below.

Data Sources and Preprocessing

To capture the fine-scale characteristics of cropland patterns, we developed a spatially explicit dynamic simulation framework at a 30 m resolution, integrating both driver-factor learning and patch-generation mechanisms widely used in land-use change modeling. Because all spatial datasets in this study are available at a consistent 30 m resolution, the modeling was implemented under a unified national grid system, which helps preserve the geometric properties and local heterogeneity of cropland patches. Compared with land-use simulations conducted at kilometer-scale resolutions, the 30 m resolution enables a more accurate representation of the detailed spatial variation in cropland distribution, although it substantially increases the computational demands of data processing and model execution.

To ensure spatial consistency across data sources, all raster datasets were standardized to the spatial reference system of the baseline cropland map, including resampling to a uniform 30 m resolution, clipping to a consistent spatial extent, and applying an identical projection. To avoid scale distortions introduced by low-resolution variables, only datasets matching the baseline 30 m resolution were used; no downscaling procedures or low-accuracy variables were incorporated into model training.

In constructing the driver-factor system for cropland change, we considered both natural terrain conditions and human activities, forming a multi-category driver-factor database. (Supplementary Table 10). The selection of drivers followed insights from previous studies while balancing data accuracy and spatial coverage[8,9] Two major groups of factors were included: (1) natural environmental drivers—digital elevation model (DEM), slope, and distance to rivers; and (2) socio-economic drivers—distance to prefecture-level city centers, distance to major roads, and distance to railways. All distance-based drivers were derived by calculating Euclidean distance from the corresponding vector datasets, producing continuous rasters aligned with the 30 m grid to represent spatial accessibility and potential development pressure at the pixel level.

To eliminate differences in units and improve numerical stability during model training, we applied min–max normalization to all driver variables, mapping their values to the range [0, 1].

$$x' = \frac{x - min(x)}{max(x) - min(x)} \tag{7-1}$$

where x is the original variable value and x' is the normalized value.

Cropland Expansion Driver Extraction

In constructing the spatial probability of cropland expansion, we followed the land-expansion analysis framework proposed by Liang et al. (2021), which transforms the identification of land-use change into a binary classification task[10]. Specifically, by overlaying land-use datasets from two periods, pixels that transitioned from non-cropland to cropland were identified and defined as positive samples, representing the spatial characteristics of newly added cropland. Pixels within the same evolutionary range that did not convert to cropland but were involved in land-use dynamics were defined as negative samples, providing contrasting conditions for learning where cropland expansion does not occur.

During the driver-factor extraction stage, we employed a Random Forest classifier to characterize the nonlinear relationships between multiple spatial drivers and cropland expansion. Random Forests consist of multiple decision trees capable of handling high-dimensional variables, capturing interactions among drivers, and maintaining strong robustness to noise. For pixel i, let x denote its vector of driving factors, and let the forest contain M decision trees. The prediction of the n-th decision tree based on x is represented by $h_n(x)$, where $h_n(x)$ = 1 indicates that the pixel is predicted to convert to cropland in the next period, and $h_n(x)$ = 0 indicates no expansion. Based on the voting results of all decision trees, the probability that pixel i will convert to cropland at the next time step, $P_{i,k}^1(x)$, can be expressed as:

$$P_{i,k}^1(x) = \frac{\sum_{n=1}^{M} I(h_n(x) = 1)}{M} \tag{7-2}$$

where $I(\cdot)$ is an indicator function that equals 1 when the n-th tree predicts expansion and 0 otherwise. This probability reflects the aggregated judgement of the Random Forest and represents the likelihood of cropland conversion under the given driving conditions, forming the foundational input for the subsequent cellular automata–based spatial simulation.

Future Cropland Dynamics under the Baseline Scenario

Under the baseline scenario, we followed the conventional quantity–space coupling framework widely used in land-use change modeling by integrating the Markov process with a cellular automata (CA) approach to simulate the future spatial pattern of cropland. The Markov process was used to project the quantity of each land-use category in future periods, providing a macro-level constraint on land-use demand. The CA module then allocated these quantities spatially at the pixel level based on driving factors, neighborhood structure and spatial competition, thereby coupling macro-scale land-use demand with local spatial processes.

(1) Macro-level Demand Projection Using the Markov Process

The Markov process analyzes land-use data from two time periods to construct a transition probability matrix that describes the likelihood of conversion between land-use categories, thereby enabling the projection of future land-use quantities. Its basic form is expressed as:

$$A_{t+1} = A_t P \tag{7-3}$$

Where A_t is the vector of land-use areas at time t.

$$A_t = [A_{1,t}, A_{2,t}, \ldots, A_{n,t}] \tag{7-4}$$

with each element representing the area of land-use types 1 to n. P denotes the land-use transition probability matrix, in which each element P_{ij} represents the probability of land-use type i converting to type j during a transition step. It is calculated as:

$$P_{ij} = \frac{N_{ij}}{\sum_{j=1}^{n} N_{ij}} \tag{7-5}$$

where N_{ij} is the number of pixels that changed from type i to type j during the observation period, and n is the total number of land-use categories. Once the transition probability matrix is obtained, multi-step land-use quantity changes can be derived through matrix exponentiation:

$$A_{t+k} = A_t P^k \tag{7-6}$$

where k is the number of projection steps.

The resulting quantity vector provides the macro-level land-use demand constraints for the subsequent spatial simulation.

(2) Spatial Conversion Probability Under Quantity Constraints

In the spatial simulation, the evolution of future land-use patterns must satisfy both macro-level quantity constraints and local spatial processes. Within the CA framework, we constructed a comprehensive conversion probability for land-use type k at pixel i and iteration step t, representing the likelihood that the pixel will convert under the combined influence of driving factors, neighborhood configuration and macro-level demand. The comprehensive conversion probability $OP_{i,k}^{t}$ is defined as:

$$OP_{i,k}^{t} = P_{i,k}^{1} \times \Omega_{i,k}^{t} \times D_{k}^{t} \tag{7-7}$$

where $P_{i,k}^{1}$ denotes the probability that pixel i converts to land-use type k; D_{k}^{t} is the dynamic demand coefficient that adjusts the simulated area of land-use type k toward the macro-level target; and $\Omega_{i,k}^{t}$ is the neighborhood effect, which describes the degree of local spatial clustering around pixel i.

The neighborhood effect reflects the spatial autocorrelation of land-use types, meaning that a pixel is more likely to convert to type k if neighboring pixels already belong to k. For an $n \times n$ neighborhood window, the neighborhood effect is expressed as:

$$\Omega_{i,k}^{t} = \frac{con(c_i^{t-1} = k)}{n^2 - 1} \cdot w_k \tag{7-8}$$

where $\mathrm{con}(c_i^{t-1} = k)$ is the number of neighboring pixels belonging to type k at iteration step $t-1$; $n^2 - 1$ is the number of pixels in the neighborhood excluding the center pixel; and w_k is the spatial weight that controls the aggregation level of type k.

The dynamic demand coefficient D_{k}^{t} is formulated as:

$$D_{k}^{t} = 1 + \beta \frac{A_k^{*} - A_k^{t}}{\left|A_k^{*} - A_k^{t}\right| + A_k^{*}} \tag{7-9}$$

where β is the demand feedback coefficient that regulates the convergence speed, A_k^{t} is the simulated area of type k at iteration step t, and A_k^{*} is the target area predicted by the Markov process.

(3) Patch Generation Mechanism

During the evolution of land-use patterns, relying solely on neighborhood effects may prevent certain land-use types from forming new patches in previously unoccupied areas, thereby reducing the ecological realism of the simulated spatial pattern. To address this issue, a *patch generation* mechanism was incorporated into the CA simulation to allow the spontaneous emergence of a limited number of new patches in areas lacking neighborhood support.

When land-use type k is completely absent from the neighborhood of pixel i (i.e., $\Omega_{i,k}^{t} = 0$), potential new patch formation is triggered through stochastic perturbation. The comprehensive conversion probability is defined as:

$$OP_{i,k}^{t} = \begin{cases} P_{i,k}^{1} \times (r \times \mu_k) \times D_k^t, & \text{if } \Omega_{i,k}^{t} = 0 \text{ and } r < P_{i,k}^{1} \\ P_{i,k}^{1} \times \Omega_{i,k}^{t} \times D_k^t, & \text{all others} \end{cases} \quad (7\text{-}10)$$

where $P_{i,k}^{1}$ is the probability of conversion to type k derived from driving factors; $r \in (0,1)$ is a random value introducing stochasticity; μ_k controls the difficulty of generating new patches of type k; $\Omega_{i,k}^{t}$ is the neighborhood effect; D_k^t is the dynamic demand coefficient.

To prevent excessive generation of new patches, a gradually decreasing conversion threshold was applied, allowing strict control of stochastic expansion during early iterations while progressively permitting more conversions later to ensure convergence[11]. When no pixel changes state in a given iteration ($N_{\text{change}} = 0$), the threshold is reduced according to:

$$\text{If } N_{change} = 0, l = l + 1, \tau_t = \tau_{t-1}\delta = \tau_0 \delta^l. \quad (7\text{-}11)$$

The conversion rule is then:

$$\begin{cases} \text{Change}, & OP_i^t \geq \tau_t, \\ \text{No change}, & OP_i^t < \tau_t. \end{cases} \quad (7\text{-}12)$$

where N_{change} is the number of pixels that successfully change state during the iteration; l is the number of threshold decay steps; τ_t is the conversion threshold at iteration t; δ is the decay coefficient; τ_{t-1} is the threshold used in the previous iteration; and OP_i^t is the comprehensive conversion probability of pixel i at time t.

Parameter Sensitivity Analysis

To systematically evaluate the influence of key parameters in the spatial evolution rules on the simulation results, five representative provinces—Jiangsu, Anhui, Jilin, Ningxia and Guizhou—were selected as experimental regions. These provinces cover typical geomorphological settings including plains, hills, humid mountain areas, arid regions and plateau–hill landscapes, thereby providing a comprehensive basis for assessing the model's applicability under diverse natural environmental conditions.

Based on the nationally unified set of driving factors, combinations of three core parameters (λ, δ, μ) were designed, resulting in 27 parameter configurations. The tested ranges were λ= 0.5–0.7, δ= 0.92–0.96 and μ= 0.001–0.005. Using land-use change during 2010–2020 as the reference period, each parameter combination was applied to the five provinces to generate simulated land-use maps for 2020. The simulation outputs were compared with the observed land-use data to compute the Figure of Merit (FoM), Overall Accuracy (OA) and the Kappa coefficient, which together provided a quantitative assessment of the performance of each parameter combination. Among these metrics, the FoM was primarily used to evaluate the relative differences among parameter sets rather than the absolute accuracy of the model.

To obtain the most robust parameter configuration for nationwide simulation, a multi-criteria ranking strategy was adopted. The median FoM across the five provinces was used as the primary selection criterion: a larger median value indicates better applicability across multiple regions. If multiple parameter combinations shared the highest median, their mean FoM values were compared, with a larger mean indicating superior overall performance. In cases where the mean values remained tied, the variance was used as the final criterion, favoring combinations with lower variance to ensure stable cross-regional performance. Based on this procedure, the parameter set λ= 0.5, δ= 0.96, μ= 0.005 was selected as the optimal configuration for the national-scale simulation, exhibiting the highest median FoM (0.36595) across the five provinces and demonstrating strong stability and adaptability across different geomorphic zones (Supplementary Table 11).

Model Implementation and Accuracy Assessment

The model was developed and executed in a Python 3.9 environment. The spatial probability extraction module was implemented using NumPy and Scikit-learn, with a Random Forest classifier used to generate the cropland expansion probability surface. The spatial dynamic evolution module employed Rasterio for raster input/output operations and NumPy for neighborhood computation and threshold decay procedures. Joblib was used to parallelize provincial simulation tasks to improve computational efficiency and scalability for large-area modeling. The national simulation was performed using a "province-level independent execution followed by final mosaicking" strategy to avoid excessive memory usage and reduce the risk of local optima arising from overly large spatial extents.

Model accuracy was evaluated using Overall Accuracy (OA), the Kappa coefficient and the Figure of Merit (FoM). OA and Kappa quantify the agreement between simulated and observed land-use maps, while FoM measures the spatial match of change locations. The validation results (Supplementary Fig. 9) show a FoM of 0.10. FoM is known to be strongly affected by spatial resolution, change intensity and validation protocols, and previous studies have reported FoM values for land-use change products typically ranging from 0.1 to 0.3[12]. Therefore, the obtained FoM of 0.10 represents a reasonable and acceptable level of change simulation accuracy under the current resolution and evaluation conditions.

Future Cropland Projection and Landscape Pattern Analysis

After completing the model accuracy assessment, the established simulation framework was used to predict the spatial distribution of cropland in China in 2040 under the baseline scenario (Supplementary Fig. 10) and the corresponding change pattern from 2020 to 2040 (Supplementary Fig. 11). The simulation output maintains the same 30-m resolution and spatial extent as the 2020 baseline dataset, ensuring full spatial comparability between periods. This prediction provides a high-resolution basis for characterizing future cropland dynamics and analyzing subsequent changes in landscape structure.

To analyse the changes in cropland spatial structure, we calculated three typical landscape indicators—MPA, PD and AI—based on the cropland data for 2020 and 2040. All three indicators were independently computed at the provincial scale using the landscapemetrics package in R, representing cropland patch size, fragmentation level and spatial aggregation, respectively (Supplementary Table 12).

Using the Freedman–Diaconis rule, we determined the bin width H and applied ±H as the threshold to classify the rate of change in each index into three change patterns: increase (I), stable (S), and decrease (D) (Supplementary Table 13). Subsequently, at the provincial level, the three landscape indexes—MPA, PD and AI—were classified accordingly to derive the corresponding change pattern type for each province, and these were then summarized to produce the provincial-scale classification of landscape structural change (Supplementary Table 14).

Between 2020 and 2040, the spatial patterns of change in the three cropland landscape indexes indicate that the landscape structure in most provinces remains generally stable (Supplementary Fig. 12). The proportions of the stable (S) category for MPA, PD and AI are 61.29%, 48.39% and 51.61%, respectively, suggesting that patch size, fragmentation and aggregation levels exhibit limited variation in the majority of provinces. Meanwhile, 32.26% of provinces show an increasing trend in MPA, 38.71% show a decreasing trend in PD, and 29.03% show an increasing trend in AI, indicating that some regions are experiencing larger patch sizes, reduced fragmentation or enhanced aggregation. Overall, China's future cropland landscape is dominated by structural stability, although moderate adjustments still occur.

The combined classification of the three indexes further reveals the spatial trajectories of cropland landscape evolution. The "structurally stable" type (S–S–S) is mainly distributed across most provinces in East, Central and North China, where all three indexes remain stable with minimal structural change. The "aggregation-enhancing" type (I–D–I) is concentrated in the southeastern coastal region and parts of central China, characterized by increasing patch size, decreasing patch numbers and enhanced aggregation, suggesting a shift toward more contiguous and intensified cropland configurations. The "intensified fragmentation" type (D–I–D) appears only in Heilongjiang and Liaoning, where decreasing patch size, increasing patch numbers and declining aggregation indicate a worsening level of fragmentation.

Overall, cropland landscape evolution in China is characterized by a predominance of stability, emerging intensification trends in the eastern and parts of the central region, and locally aggravated fragmentation in the northeast. These spatial differences reflect heterogeneous trajectories of cropland use and landscape structural adjustment across regions, offering important insights for future region-specific cropland protection and landscape optimization strategies.

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9. Li, X. C. *et al.* A cellular automata downscaling based 1 km global land use datasets (2010-2100). *Sci Bull* **61**, 1651-1661 (2016).
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Supplementary Table 10–Supplementary Table 14:

Supplementary Table 10 | Input datasets for the 2040 cropland simulation.

Category	Data	Year	Resolution	Data resource
Natural environment	DEM (Digital Elevation Model)	2020	30 m	NASA SRTM1 v3.0
	Slope	2020	30 m	(https://lpdaac.usgs.gov/products/srtmgl1v003/)
Socio-economic factors	Distance torivers	2020	30 m	OpenStreetMap
	Distance to cities	2020	30 m	(https://www.openstreetmap.org/)
	Distance to mainroads	2020	30 m	
	Distance to railways	2020	30 m	
Land use data	Cropland and non-cropland map	2010,2020	30 m	Produced in this study based on remote sensing interpretation

Supplementary Table 11 | Summary of FoM statistics for the 27 parameter combinations (λ, δ, μ) across the five representative provinces.

λ	δ	μ	FoM (median)	FoM (mean)	FoM (variance)
0.5	0.96	0.005	0.365950706	0.366184386	0.000978135
0.5	0.96	0.003	0.365037223	0.365590437	0.00098228
0.5	0.92	0.003	0.364601233	0.366077786	0.000936174
0.5	0.92	0.005	0.364352387	0.366466332	0.000980118
0.5	0.94	0.005	0.364303188	0.366462993	0.001027998
0.5	0.92	0.001	0.364199188	0.365884999	0.000983797
0.5	0.94	0.001	0.364053797	0.366606312	0.001029956
0.5	0.96	0.001	0.363583585	0.366245624	0.001030562
0.5	0.94	0.003	0.363138299	0.3667156	0.000972018
0.6	0.92	0.003	0.365674704	0.365539231	0.000978896
0.6	0.96	0.003	0.365261416	0.366272063	0.000986535
0.6	0.96	0.001	0.36463788	0.365983083	0.000997214
0.6	0.94	0.003	0.364368316	0.36638105	0.000987051
0.6	0.92	0.001	0.363713427	0.366186574	0.000966423
0.6	0.94	0.001	0.363604703	0.366453206	0.000954513
0.6	0.92	0.005	0.363418107	0.366007779	0.000984248
0.6	0.94	0.005	0.363119751	0.366546704	0.000944405
0.6	0.96	0.005	0.363058244	0.366356501	0.000955257
0.7	0.96	0.003	0.365228481	0.366015894	0.000980037
0.7	0.94	0.001	0.365182889	0.365768114	0.000991507
0.7	0.92	0.005	0.365125186	0.365970382	0.001016164
0.7	0.94	0.005	0.365040352	0.365981059	0.001004144
0.7	0.92	0.003	0.364755171	0.365988231	0.000990967
0.7	0.94	0.003	0.364507181	0.365843685	0.000981438
0.7	0.92	0.001	0.36421249	0.366441628	0.000932203
0.7	0.96	0.005	0.363662527	0.366264252	0.000987476
0.7	0.96	0.001	0.363176336	0.36625195	0.000978286

Notes: FoM statistics (median, mean, variance) for the 27 parameter combinations (λ, δ, μ) across five provinces. Bold values indicate the highest FoM median, representing the optimal parameter set.

Supplementary Table 12 | Provincial landscape indexes in 2040.

province	MPA	PD	AI
Anhui	69.16883926	1.44573772	96.96177959
Beijing	16.50059736	6.060386651	92.21570716
Chongqing	7.56617653	13.21671515	85.5405915
Fujian	4.737688191	21.10734096	83.90536685
Gansu	32.45469	0.7572932	93.59637
Guangdong	12.20997274	8.190026477	90.19996932
Guangxi	10.58471825	9.4475826	90.72927783
Guizhou	4.134730843	24.18537114	79.95821417
Hainan	4.401365	3.198759	82.76022
Hebei	36.66127567	2.72767377	96.19483501
Heilongjiang	13.57867	1.398997	89.23713
Henan	82.25082499	1.215793276	97.36932817
Hubei	25.97365828	3.850054503	94.90635749
Hunan	15.8430457	6.311917664	91.39749621
Jiangsu	98.28854149	1.017412594	96.68840434
Jiangxi	19.56286929	5.111724589	91.73330675
Jilin	37.94444159	2.635432116	94.85890533
Liaoning	9.465577718	10.56459553	89.56480865
Neimenggu	10.65205385	0.640115591	59.23055983
Ningxia	16.67091081	5.998472499	92.16598869
Qinghai	5.179666717	19.30626148	88.20868179
Shaanxi	7.6078835	13.14426016	88.88046691
Shandong	67.0007146	1.492521395	96.51555161
Shanghai	57.84399395	1.728787955	94.28717328
Shanxi	20.697193	4.831573055	93.59622349
Sichuan	6.50418956	15.37470565	86.08352325
Tianjin	77.85407376	1.284454302	96.59422578
Xinjiang	41.8607001	0.10583875	95.3859791
Xizang	9.182418586	22.67072666	87.06430276
Yunnan	6.097463757	16.40026148	86.37547139
Zhejiang	11.98281069	8.345287479	89.95390072

Supplementary Table 13 | Division of change patterns (simulation).

Stages	Change pattern	Landscape indexes and agricultural production indicators		
		AI	PD	MPA
Simulation	I	>0.02	>0.28	>0.45
	S	-0.02~0.02	-0.28~0.28	-0.45~0.45
	D	<-0.02	<-0.28	<-0.45

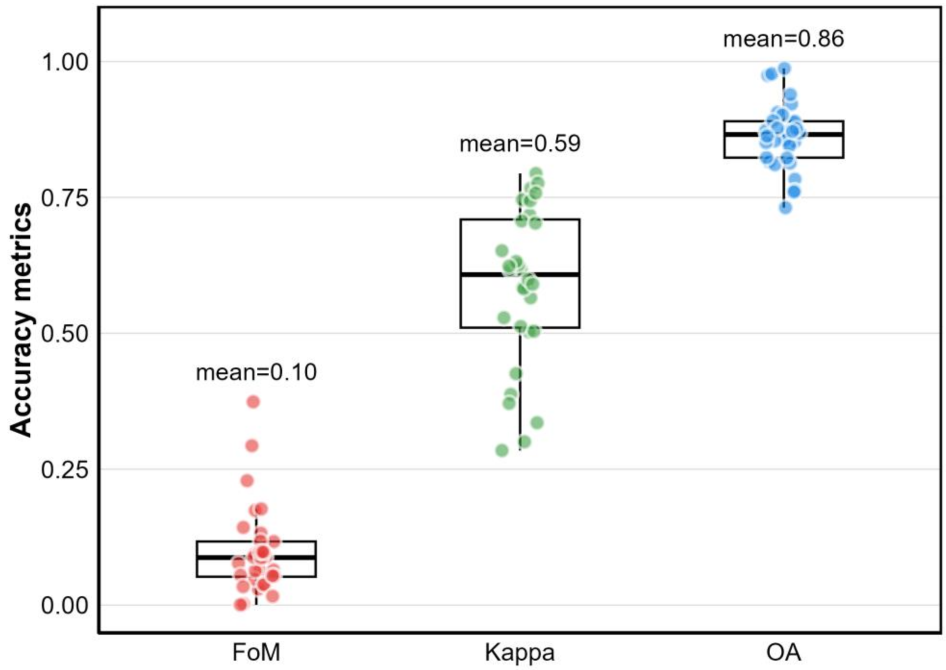
Notes: The numbers in the table represent the threshold "H". AI: Aggregation Index; PD: Patch Density; MPA: Mean Patch Area; F: Fertilizer use; M: Total machinery power usage; Y: Crop yield; W: Irrigation water; I: Increase; S: Stable; D: Decrease

Supplementary Table 14 | Change patterns for 31 provincial-level administrative regions in 2040.

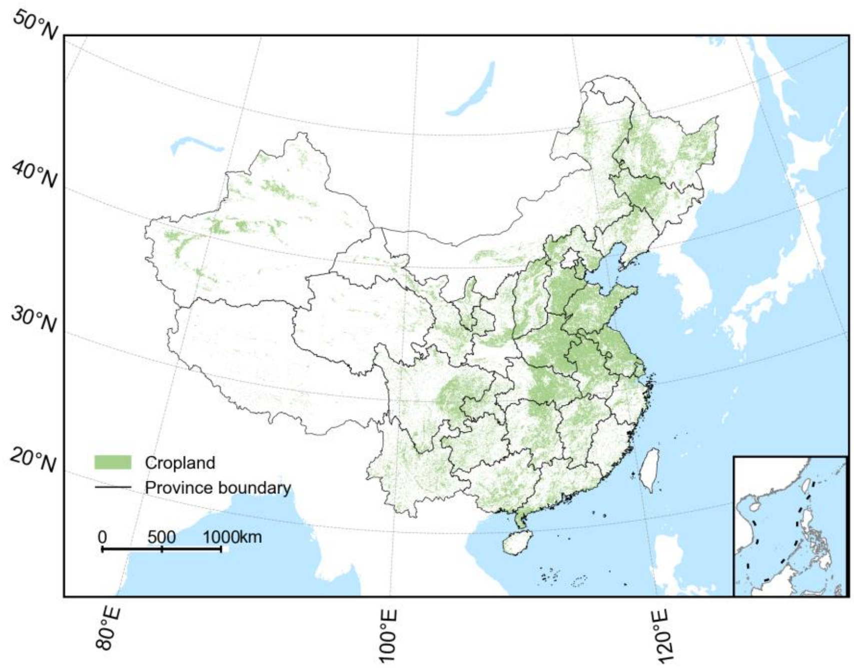
Agricultural production zone	Provincial administrative region	Change patterns		
		MPA	PD	AI
NCP	Heilongjiang	D	I	D
	Jilin	I	D	S
	Liaoning	D	I	D
NASR	Inner Mongolia	S	I	D
	Xinjiang	S	D	S
	Gansu	I	D	I
	Ningxia	I	D	S
HHHP	Beijing	S	S	S
	Tianjin	I	D	S
	Hebei	S	S	S
	Shandong	S	S	S
	Henan	S	S	S
LP	Shaanxi	S	S	S
	Shanxi	I	D	I
QTP	Qinghai	S	S	I
	Tibet	I	I	I
MLYP	Anhui	S	S	S
	Jiangsu	S	S	S
	Jiangxi	S	D	S
	Zhejiang	S	S	S
	Hunan	S	S	S
	Shanghai	I	D	I
	Hubei	I	D	I
SCB	Sichuan	S	S	S
	Chongqing	S	S	D
YGP	Yunnan	S	S	I
	Guizhou	S	S	D
	Guangxi	S	S	S
SC	Guangdong	I	D	I
	Fujian	S	S	S

Note: 'I' represents an increase in the change pattern, 'S' represents a stable change pattern, and 'D' represents a decrease in the change pattern.

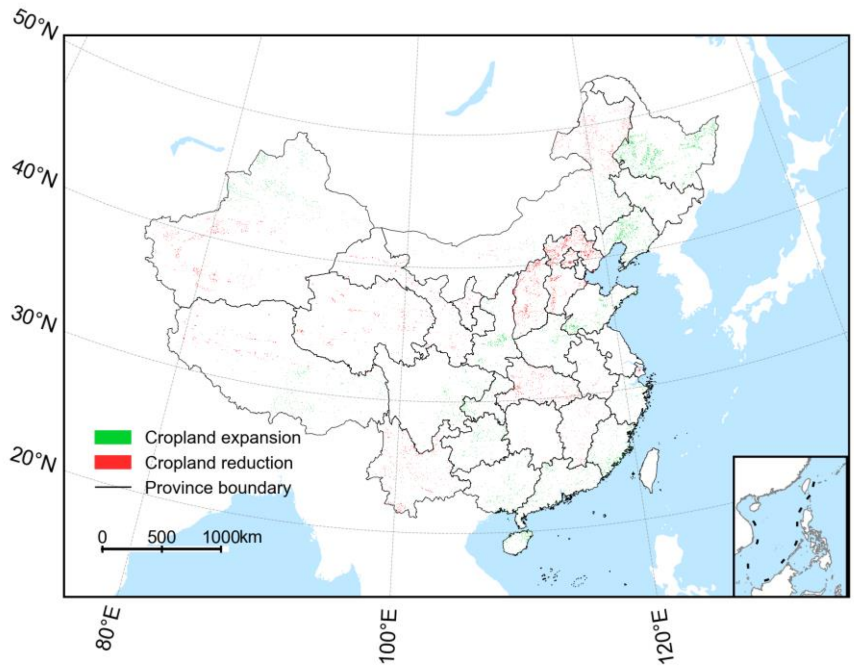
Supplementary Fig. 9–Supplementary Fig. 12：



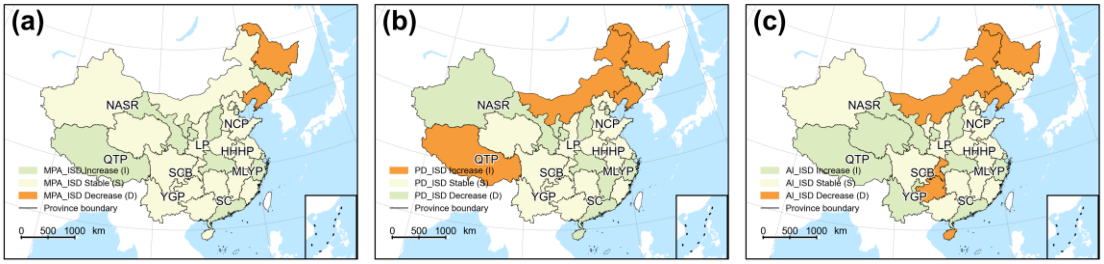
Supplementary Fig. 9 | Accuracy metrics of the land-use simulation model. Box plots show the distribution of three accuracy indicators — the Figure of Merit (FoM), Kappa coefficient, and Overall Accuracy (OA) — across all provinces (n = 31). Each dot represents the model performance for one province. Boxes indicate the interquartile range (IQR; 25th–75th percentiles), center lines denote the median, and whiskers extend to 1.5 × IQR. The mean value for each metric is annotated above the corresponding box.



Supplementary Fig. 10 | Spatial distribution of cropland in China in 2040.



Supplementary Fig. 11 | Spatial distribution of cropland change in China from 2020 to 2040.



Supplementary Fig. 12 | Spatial patterns of change patterns for 31 provincial-level administrative regions during 2020–2040. (a) shows the change patterns of mean patch area (MPA), (b) presents the change patterns of patch density (PD), and (c) illustrates the change patterns of the aggregation index (AI). 'I' represents an increase in the change pattern, 'S' represents a stable change pattern, and 'D' represents a decrease in the change pattern.

Additional Suggestions:

Comment 03: Considering the global nature of agricultural intensification, it would be beneficial to position your findings within the broader international context. How do the trends observed in China compare to other countries that have pursued sustainable agricultural intensification? Can China learn from global experiences, or does it offer unique insights that could benefit other regions? A brief comparison with international trends could enhance the relevance of your findings and highlight the broader applicability of your study.

Reply: Thank you for your valuable suggestion. To better place our findings in an international context, we have added a comparative discussion in the revised manuscript, highlighting the differences between China's sustainable agricultural intensification pathway and those of developed countries such as those in Europe and the United States. We also emphasized that China's experience under a smallholder-dominated agricultural system may offer useful references for other developing countries facing similar challenges. Please check **Lines 331-344** in the revised manuscript.

Lines 331-344: "These findings highlight the distinct pathway of sustainable agricultural intensification in China compared to many developed countries. In Europe and the United States, intensification has largely built upon a pre-existing foundation of large-scale farms, with its main driving force being technological innovation—such as precision agriculture, conservation tillage, and digital farm management systems[51]. These approaches focus on enhancing efficiency and reducing environmental impacts, representing a typical "technology-driven" model of intensification.

By contrast, China tends to prioritize land consolidation before promoting technological adoption. Historically, China's agricultural system has been dominated by highly fragmented smallholder farming[52]. In this context, institutional and policy support for cropland consolidation has played a central role in driving sustainable agricultural intensification. Unlike the technology-led strategies in developed countries, China's policy-oriented approach offers a distinctive model that may provide valuable insights for other developing countries facing similar smallholder-related challenges."

References:

51 Lindblom, J. *et al.* Promoting sustainable intensification in precision agriculture: review of decision support systems development and strategies. *Precis Agric* **18**, 309-331 (2017).

52 Chen, M. *et al.* Do small and equally distributed farm sizes imply large resource misallocation? Evidence from wheat-maize double-cropping in the North China Plain. *Food Policy* **112** (2022).

Comment 04: The manuscript would benefit from a clearer articulation of its unique contribution to the field. What makes this study innovative? How does it advance the current understanding of sustainable intensification, particularly in the Chinese context? It would be helpful to explicitly outline the key innovations of your study in the conclusion, ensuring that the most significant findings are clearly communicated to the reader.

Reply: Thank you for your valuable suggestion. We have added a **Final remarks** section in the revised manuscript to clarify the key innovations of this study, helping readers better understand its most important findings. Please check **Lines 441–451** in the revised manuscript.

Lines 441-451:

"**Final remarks**

The sustainable transformation of agricultural intensification in China fundamentally depends on the spatial optimization of cropland patterns. As cropland becomes increasingly consolidated and contiguous, the reliance on high-intensity inputs such as chemical fertilizers and machinery significantly decreases, resulting in improved resource use efficiency. We provide theoretical justification and empirical evidence supporting the hypothesis that cropland consolidation is a key driver of the shift from unsustainable to sustainable intensification in China. These findings offer concrete proof of China's progress toward sustainable agricultural intensification and may serve as a valuable reference for other smallholder-dominated countries and regions pursuing similar pathways."

Comment 05: In the final paragraph of the results section, you mention the challenges of sustainable agricultural intensification in China. However, there is little explanation of how your study's findings can help address these challenges. While the study demonstrates the current state of agricultural intensification, it would be useful to discuss how your findings can inform potential solutions to these challenges, such as land degradation or the need for policy reforms. By offering suggestions for practical applications, your work could provide a clearer pathway toward addressing these critical issues.

Reply: Thank you for your suggestion. Based on our findings, we argue that optimizing the spatial configuration of cropland should be prioritized. Accordingly, we have supplemented the Results and Discussion section with insights into potential land policy reforms and proposed practical recommendations to address the challenges of sustainable intensification. Please check **Lines 413-424** in the revised manuscript.

Lines 413-424: "In addition to water resource management, optimizing the spatial configuration of cropland is also a crucial pathway toward achieving sustainable intensification. Such optimization is not merely a structural adjustment, but a spatial management strategy that balances productivity, resource efficiency, and environmental protection. It offers a potential solution to the bottlenecks in transitioning from conventional to sustainable agricultural intensification[66]. Spatial optimization of cropland can amplify the effectiveness of existing national initiatives—such as soil testing-based fertilization, high-standard farmland construction, and irrigation reform—by enabling their efficient implementation across larger, contiguous land units. For example, measures such as incentives for land transfer, ecological compensation in consolidated areas, and cross-regional coordination mechanisms for cropland can simultaneously enhance productivity and promote ecological restoration[67]."

References:

66 Verburg, P. H. *et al.* Land system change and food security: towards multi-scale land system solutions. *Curr Opin Env Sust* 5, 494-502 (2013).

67 Fei, R. L. *et al.* How land transfer affects agricultural land use efficiency: Evidence from China's agricultural sector. *Land Use Policy* **103** (2021).

Reviewer #2:

General comment: The authors have carefully addressed all of my previous concerns, and the re vised manuscript has been substantially improved. The responses are clear and convincing, and the revisions have resolved the issues I raised. I believe the manuscript is now suitable for publi cation in its current form.

Reply: We sincerely thank the reviewer for the positive evaluation. We appreciate your recognition of our revisions. Thank you for your constructive feedback and support.

Response to reviewer's comments:

Reviewer #1:

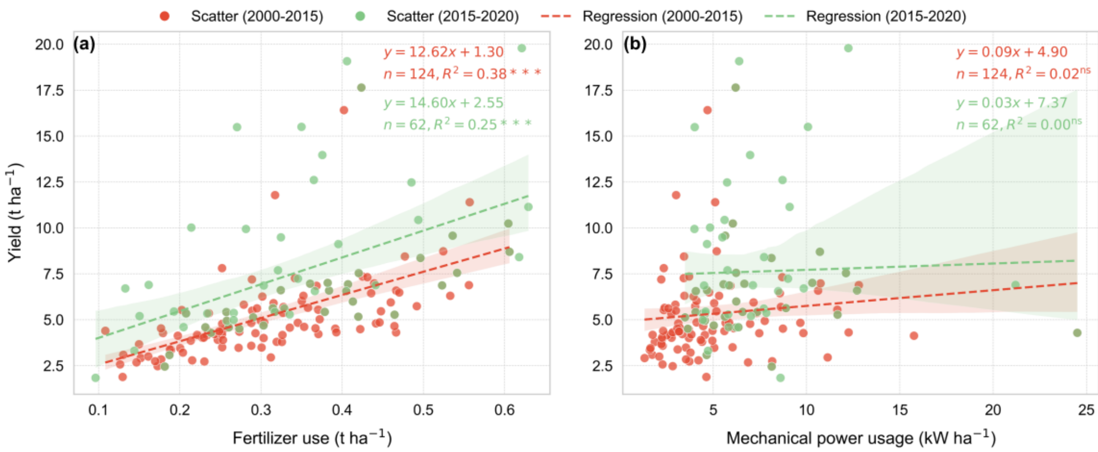
General comment: The authors have addressed my previous concerns well. However, I have a few remaining minor points:

Reply: Thank you very much for your positive evaluation of our revisions. We have carefully addressed the remaining minor points, and the manuscript has been revised accordingly.

Comment 01: Line 262: Please rethink or further elaborate on the statement attributing crop yield increases to the extensive use of fertilizers and machinery. It is currently unclear how the provided data or analysis leads directly to this conclusion.

Reply: Thank you for this helpful comment. In our framework, sustainable intensification is interpreted through the co-occurrence of changes in yield and input indicators across regions and periods. To improve transparency and avoid overstatement, we made two revisions. First, we replaced causal language (e.g., "primarily dependent on") with an association-based description, and refined the wording to reflect that fertilizer application shows a clearer yield-related signal than agricultural machinery use in our bivariate analyses. Second, we added **Supplementary Figure 2** to explicitly present the period-specific scatterplots and univariate regression results supporting this interpretation. Please see **Lines 237–239** in the revised manuscript and **Supplementary Figure 2** in the revised supplementary materials.

Lines 237-239: "This observation suggests that the yield increase during this period was closely associated with rising fertilizer application, alongside concurrent increases in machinery power usage (Supplementary Figure 2) [46]."



Supplementary Figure 2 | Correlations between yield and agricultural production indicators during the contraction (2000–2015) and recovery (2015–2020) periods. The scatter plots illustrate the linear regression analysis of yield (t ha^{-1}) in response to (a) fertilizer use (t ha^{-1}) and (b) machinery power usage (kW ha^{-1}). Red data points and dashed lines represent the contraction period (2000–2015), while green data points and dashed lines correspond to the recovery period (2015–2020). Statistical annotations include the linear regression equation, sample size (n), coefficient of determination (R^2), and significance levels. Significance is denoted as follows: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, and ns indicates not significant ($p \geq 0.05$). Shaded bands around the regression lines represent the 95% confidence intervals.

Comment 02: To improve transparency, please include a table summarizing the correlation between cropland landscape configuration and agricultural input intensity. This table should explicitly report the sample size, the specific model type used, p-values, and R2 coefficients.

Reply: Thank you for this constructive suggestion. In the previous version, we reported the statistical significance of these bivariate relationships (p-values) in **Supplementary Figure 3**. Following the reviewer's recommendation and to further improve transparency and ease of reference, we have now added **Supplementary Table 4** to provide a consolidated summary of the results.

Supplementary Table 4 reports, for each landscape index and period, the sample size (N), the model type (univariate ordinary least squares, OLS), the coefficient of determination (R^2), and the corresponding p-values. This supplementary table has been referenced in the revised manuscript accordingly. Please check **Lines 278-281** in the revised manuscript and **Supplementary Table 4** in the revised supplementary materials.

Lines 278-281: "To further verify whether cropland concentration contributes to improved resource use efficiency, we conducted a correlation analysis between cropland landscape configuration indexes and agricultural input intensity indicators across 31 provincial-level administrative units (Fig. 5, Supplementary Figure 3, Supplementary Table 4)."

Supplementary Table 4 | Correlation between cropland landscape configuration and agricultural input intensity.

Period	Landscape index	Input intensity	N	Model	R^2	*p*-value
2000–2015	MPA	Fertilizer Intensity	124	OLS (univariate)	0.135	< 0.001
2015–2020		Fertilizer Intensity	62	OLS (univariate)	0.028	0.194
2000–2015		Mechanization Intensity	124	OLS (univariate)	0	0.957
2015–2020		Mechanization Intensity	62	OLS (univariate)	0.037	0.135
2000–2015		Irrigation Intensity	124	OLS (univariate)	0.079	0.002
2015–2020		Irrigation Intensity	62	OLS (univariate)	0.184	< 0.001
2000–2015	AI	Fertilizer Intensity	124	OLS (univariate)	0.092	< 0.001
2015–2020		Fertilizer Intensity	62	OLS (univariate)	0.034	0.153
2000–2015		Mechanization Intensity	124	OLS (univariate)	0.065	0.004
2015–2020		Mechanization Intensity	62	OLS (univariate)	0.312	< 0.001
2000–2015		Irrigation Intensity	124	OLS (univariate)	0.160	< 0.001
2015–2020		Irrigation Intensity	62	OLS (univariate)	0.401	< 0.001
2000–2015	PD	Fertilizer Intensity	124	OLS (univariate)	0.037	0.033
2015–2020		Fertilizer Intensity	62	OLS (univariate)	0.030	0.181
2000–2015		Mechanization Intensity	124	OLS (univariate)	0.207	< 0.001
2015–2020		Mechanization Intensity	62	OLS (univariate)	0.50	< 0.001
2000–2015		Irrigation Intensity	124	OLS (univariate)	0.148	< 0.001
2015–2020		Irrigation Intensity	62	OLS (univariate)	0.377	< 0.001

Notes: The table summarizes bivariate correlations between cropland landscape configuration and agricultural input intensity based on univariate ordinary least squares (OLS) regressions. Reported statistics include sample size (N), coefficients of determination (R^2), and *p*-values.

Comment 03: Line 360: Please carefully re-verify Reference 53. This citation might not directly support the statement. Furthermore, please re-examine how the authors of that study determined and defined "farm size".

Reply: Thank you for the careful examination. Ref. 53 draws on survey-based evidence to distinguish field size from large-scale farming and highlights that, even under fragmented field conditions, there is substantial potential to develop larger-scale farm operations through land transfer and management integration.

In our manuscript, cropland size refers to the physical size of individual cropland parcels (i.e., field size in Ref. 53), whereas farm size corresponds to the operated land area under unified management, including both contracted land and transferred-in land. Our intention in citing Ref. 53 was to emphasize this scale mismatch and the associated potential for scaling up agricultural operations without necessarily enlarging individual fields.

To avoid further misunderstanding, we have revised the sentence accordingly. Please check **Lines 320-323** in the revised manuscript.

Lines 320-323: “The discrepancy between cropland size and farm size—where farm size refers to the operated land area under unified management (including contracted land plus transferred-in land)—highlights the potential for scaling up agricultural operations through management integration even under fragmented field conditions[53].”

This manuscript applies well-established methods and datasets to validate an intuitively reasonable hypothesis rather than providing novel theoretical insights or methodological innovations. While the study offers a detailed analysis of cropland distribution and sustainable intensification using remote sensing and machine learning techniques, the approach—including RF classification, vegetation indices, and spatial-temporal analysis—is widely documented in the literature. The findings, though informative, primarily confirm expected trends rather than addressing an unresolved research gap.

Major Concerns:

1. The study follows conventional workflows without introducing substantial methodological advancements. It primarily validates known patterns rather than proposing a new framework or addressing a critical gap in sustainable intensification research. The authors should consider whether the study could go beyond confirming expected trends to tackle an unresolved challenge in agricultural intensification.
2. The use of the Freedman-Diaconis rule for defining change patterns in landscape indices and agricultural production indicators raises concerns. This rule is traditionally used for histogram binning, and its application to classify agricultural change patterns—especially with spatial-temporal variations—needs further justification. How does it account for the temporal dynamics and spatial heterogeneity of agricultural change?
3. The classification of agricultural regions is inconsistent. While the study initially divides China into nine agricultural production zones, Fig. 3 presents results at the provincial level. The rationale behind this discrepancy should be clarified.
4. The study generates cropland maps across five periods but does not justify why existing cropland datasets were not used. If the newly created maps offer higher classification accuracy, this advantage should be explicitly demonstrated rather than assumed based on similarity with previous results.

Additional Comments:

1. The introduction provides a strong background on food security and agricultural intensification but could be better structured. A suggested logical flow:
   i. Global food security challenges and agricultural intensification
   ii. Environmental concerns related to intensification
   iii. China's specific situation (e.g., excessive chemical use, fragmented farmland)
   iv. Limitations of current evaluation methods and the need for remote sensing
   v. Research gap and contributions of this study
2. Abbreviations: Once an acronym is introduced, the full term should not be repeated.
3. Supplementary Fig. 4 appears to be a direct screenshot from GEE's console, which seems unpolished. A more refined presentation is recommended.
4. Figs. 1 & 4: High-saturation colors should be avoided for clarity.