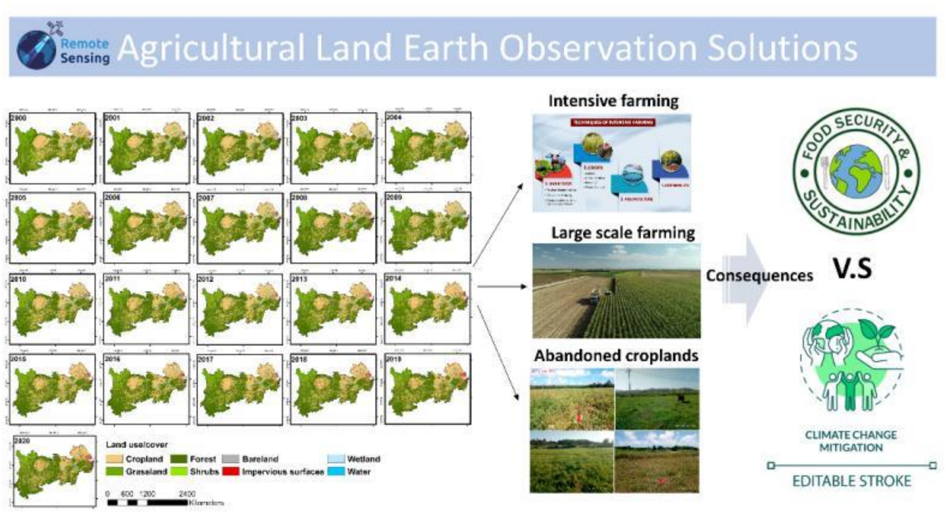
Spatiotemporal analysis of cropland production and its trade-off with climate regulation across China



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Abstract

The World Food Summit and the Paris Agreement have highlighted the vital need to sustain food production and to mitigate the effects of climate change. This represents a pivotal moment in the development of present and future agricultural and food systems, further emphasized by the United Nations' 2015 pledge to achieve Zero Hunger (SDG 2) and Climate Action (SDG 13) as key elements of the Sustainable Development Goals (SDGs). Global food security is increasingly at risk due to various challenges, including population growth, rapid urbanization, unsustainable resource use, and the negative effects of climate change on crop production, despite improvements in agricultural productivity. These problems are worsened by changing diets that favor resource-intensive foods, resulting in substantial environmental damage and highlighting the crucial link between farming practices and sustainability. Cropland plays a crucial role not only in food production but also in providing essential ecosystem services, thus contributing significantly to several SDGs. This emphasizes the urgent need to adopt sustainable farming practices in the face of growing land-use conflicts. Furthermore, it is critical to integrate technological innovations and interdisciplinary research to improve land management strategies. This thesis carefully investigates China's unique position in the global agricultural landscape, analyzing the complex tradeoff between food security and environmental sustainability using various data sources, including earth observation datasets, statistical analyses, and academic literature. China's rapid urbanization has led to substantial changes in agricultural land-use patterns, particularly in main grain-producing areas like the Yangtze River Basin. These changes have significant implications for China's agricultural production and its crucial role in the global food supply chain, highlighting the need for sustainable farming practices to address the growing demand for global resources.

Chapter 2 explores strategies of cropland intensification and large-scale utilization to meet China's growing food demand. It utilizes the Logarithmic-Mean-Divisia-Index (LMDI) analysis, along with statistical and land cover data, to assess the impact of cropland intensification (i.e. crop yield and Multiple Cropping Index) and large-scale utilization (i.e. Mean Parcel Size and Number of Parcels) on crop production at both national and local scale. The analysis indicates that advancements in agricultural technology and management practices that increase yield and enable multiple harvests per year can significantly boost crop production. This is essential for overcoming the logistical and environmental challenges associated with diverse cropland sizes and ensuring food security. The chapter concludes that, notwithstanding these obstacles, optimizing yield and implementing multiple cropping can be crucial in sustainably meeting China's growing food needs.

Chapter 3 examines spatial temporal dynamics of cropland abandonment and recultivation between 2000 and 2020 across the Yangtze River Basin. Using remote sensing, the study reveals a notable trend of cropland abandonment, particularly in regions in regions characterized by gentle slopes. Notably, a substantial proportion (74%) of this abandoned land has been recultivated for agricultural purposes,

demonstrating the region's resilience and adaptability in land use. This chapter presents novel insights into dynamics of agricultural land use, offering a foundation for future research and policy recommendations aimed at restoring abandoned cropland and fostering sustainable farming methods. The results emphasize the crucial role of policy support, technological advancements, and adaptive farming practices in promoting the recultivation of abandoned lands.

Based on cropland abandonment and recultivation maps conducted in Chapter 3, Chapter 4 explores the tradeoffs between cropland production and climate regulation. The study reveals that, using the Carbon Sequestration module of InVEST model (Integrated Valuation of Ecosystem Services and Tradeoffs), cropland abandonment led to a substantial increase in carbon stock, storing an additional total of 182.3 million tons of C between 2002 and 2020. Nevertheless, this environmental benefit comes at the cost of a 13.47 million ton decrease in grain production. Spearman correlation analysis revealed a significant trade-off at the provincial level between carbon stock change and grain yield change, further analysis indicated diverse impacts across regions at grid level. This study highlights the pressing need for policies that can balance the dual goals of climate change mitigation through enhanced carbon storage and food security through optimized grain production. The findings support the development of refined land management practices that carefully equilibrate environmental benefits and agricultural productivity.

Overall, this thesis contributes to the discourse on sustainable land use planning in China, providing empirical evidence and strategic insights to address the complex challenges of ensuring food security, enhancing crop production efficiency, and mitigating climate change impacts.

Abstrait

Le Sommet mondial de l'alimentation et l'Accord de Paris ont mis en lumière la nécessité vitale de soutenir la production alimentaire et d'atténuer les effets du changement climatique. Cela représente un moment crucial dans le développement des systèmes agricoles et alimentaires actuels et futurs, souligné par l'engagement de l'ONU en 2015 à atteindre la Faim Zéro (ODD 2) et l'Action Climatique (ODD 13) comme éléments clés des Objectifs de Développement Durable (ODD). La sécurité alimentaire mondiale est de plus en plus menacée par divers défis, y compris la croissance démographique, l'urbanisation rapide, l'utilisation non durable des ressources et les effets négatifs du changement climatique sur la production agricole, malgré les améliorations de la productivité agricole. Ces problèmes sont aggravés par des régimes alimentaires changeants favorisant des aliments gourmands en ressources, entraînant des dommages environnementaux substantiels et soulignant le lien crucial entre les pratiques agricoles et la durabilité. Les terres agricoles jouent un rôle essentiel non seulement dans la production alimentaire mais aussi dans la fourniture de services écosystémiques essentiels, contribuant ainsi de manière significative à plusieurs ODD. Cela souligne le besoin urgent d'adopter des pratiques agricoles durables face aux conflits croissants d'utilisation des terres. De plus, il est crucial d'intégrer les innovations technologiques et la recherche interdisciplinaire pour améliorer les stratégies de gestion des terres. Cette thèse examine attentivement la position unique de la Chine dans le paysage agricole mondial, analysant le compromis complexe entre la sécurité alimentaire et la durabilité environnementale à l'aide de diverses sources de données, y compris des ensembles de données d'observation de la Terre, des analyses statistiques et la littérature académique. L'urbanisation rapide de la Chine a conduit à des changements substantiels dans les modes d'utilisation des terres agricoles, en particulier dans les principales zones de production céréalière comme le bassin du fleuve Yangtze. Ces changements ont des implications significatives pour la production agricole de la Chine et son rôle crucial dans la chaîne d'approvisionnement alimentaire mondiale, soulignant la nécessité de pratiques agricoles durables pour répondre à la demande croissante de ressources mondiales.

Le chapitre 2 explore les stratégies d'intensification des terres agricoles et d'utilisation à grande échelle pour répondre à la demande alimentaire croissante de la Chine. Dans ce chapitre, on utilise l’analyse Logarithmic-Mean-Divisia-Index (LMDI), ainsi que des données statistiques et de couverture des terres, pour évaluer l'impact de l'intensification des terres agricoles (c'est-à-dire le rendement des cultures et l'indice de cultures multiples) et de l'utilisation à grande échelle (c'est-à-dire la taille moyenne des parcelles et le nombre de parcelles) sur la production agricole à l'échelle nationale et locale. L'analyse indique que les avancées technologiques et les pratiques de gestion agricoles qui augmentent le rendement et permettent plusieurs récoltes par an peuvent considérablement augmenter la production agricole. Cela est essentiel pour surmonter les défis logistiques et environnementaux associés à la diversité des tailles des terres agricoles et garantir la sécurité alimentaire. Le chapitre conclut que, malgré ces obstacles, l'optimisation du rendement et la mise en œuvre de cultures multiples

peuvent être cruciales pour répondre durablement aux besoins alimentaires croissants de la Chine.

Le chapitre 3 examine les dynamiques spatio-temporelles de l'abandon et de la recultivation des terres agricoles entre 2000 et 2020 dans le bassin du fleuve Yangtze. En utilisant la télédétection, l'étude révèle une tendance notable à l'abandon des terres agricoles, en particulier dans les régions avec des pentes douces. Notamment, une proportion substantielle (74%) de ces terres abandonnées a été recultivée à des fins agricoles, démontrant la résilience et l'adaptabilité de la région en matière d'utilisation des terres. Ce chapitre présente de nouvelles perspectives sur les dynamiques d'utilisation des terres agricoles, offrant une base pour de futures recherches et recommandations politiques visant à restaurer les terres abandonnées et à promouvoir des méthodes agricoles durables. Les résultats soulignent le rôle crucial du soutien politique, des avancées technologiques et des pratiques agricoles adaptatives pour promouvoir la recultivation des terres abandonnées.

Basé sur les cartes d'abandon et de recultivation des terres agricoles établies au chapitre 3, le chapitre 4 explore les compromis entre la production agricole et la régulation climatique. L'étude révèle que l'abandon des terres agricoles a entraîné une augmentation substantielle du stock de carbone, stockant un total supplémentaire de 182,3 millions de tonnes de C entre 2002 et 2020 en utilisant le module de séquestration du carbone du modèle InVEST (Évaluation intégrée des services écosystémiques et des compromis). Néanmoins, cet avantage environnemental se fait au détriment d'une diminution de 13,47 millions de tonnes de la production céréalière. Une analyse de corrélation de Spearman a révélé un compromis significatif au niveau provincial entre le changement de stock de carbone et le changement de rendement céréalier, et une analyse plus approfondie a indiqué des impacts divers à l'échelle régionale. Cette étude souligne le besoin pressant de politiques qui peuvent équilibrer les objectifs doubles de la mitigation du changement climatique par une augmentation du stockage du carbone et de la sécurité alimentaire par une optimisation de la production céréalière. Les résultats soutiennent le développement de pratiques de gestion des terres raffinées qui équilibrent soigneusement les bénéfices environnementaux et la productivité agricole.

Dans l'ensemble, cette thèse contribue au discours sur la planification durable de l'utilisation des terres en Chine, en fournissant des preuves empiriques et des idées stratégiques pour relever les défis complexes de la sécurité alimentaire, de l'amélioration de l'efficacité de la production agricole et de l'atténuation des effets du changement climatique.

Resume

Yuqiao Long was born on 14 July 1992 in Sichuan, China. He was a joint PhD student at Gembloux Agro-Bio Tech, University of Liège, Belgium, and the Institute of Agricultural Resources and Regional Planning, Chinese Academy of Agricultural Sciences (CAAS). He was funded by the "China Scholarship Council Doctoral Training Program". He obtained in 2015 the Bachelor of Engineering in Remote Sensing from Chengdu University of Information Technology (China), and in 2018 the Master of Agriculture in Agricultural Resource Utilization from the Chinese Academy of Agricultural Sciences. His research focuses on the spatiotemporal dynamics of agricultural land systems, especially through the integration of Earth Observation data, geographic information systems (GIS), and statistical data, and has made notable contributions to the field of agricultural land system science (ALSS). His work includes: (i) analyzing the drivers of food production in the context of agricultural land use, (ii) monitoring spatial and temporal dynamics of cropland abandonment and recultivation based on cloud-computing platform, and (iii) assessing the impacts of these changes on key ecosystem services and their trade-offs, and advancing the Nature-based Solutions (NbS) of marginal lands. He has been actively involved in several important conferences in the field of agricultural land use. In 2024, he participated in the “Young Soil Scientists Day” and “Young Geographers Day” in Belgium by poster presentation. In 2023, he participated in the "EGU Conference" in Austria and gave an oral presentation. His research have been published in two international peer-reviewed academic articles (as first author). He has also received a number of awards from the CAAS for his learning achievements.

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Pursuing my PhD at the Water, Soil & Plant Exchanges Laboratory at Agro-Bio Tech Gembloux has been a wonderful experience. I remember stepping onto this beautiful campus as a young man full of dreams and ambitions with a big smile on my face. Standing at the door of the Abbey for the first time, I felt that I was going to make a big difference. Two years have passed, I am about to graduate, and before I leave Belgium, I am here again. Like two years ago, the buildings were still quaint, but my mindset and awareness had improved greatly. Looking back, my research and mindset went through ups and downs. I even spent one whole night sitting on a bench near the Abbey, looking up at the stars as my thoughts wandered through the universe. During my PhD studies, I believe I have grown to master how to be a good researcher and gained valuable understanding of myself and the Earth's environment.

Firstly, I would like to extend my deepest gratitude to Prof. Jeroen Meersmans for his unwavering patience and scholarly guidance throughout my time in Belgium. His approachable nature not only made my learning experience in Belgium enjoyable but also immensely enriching. I greatly admire his expertise and his serious attitude towards scientific research. Whenever I encountered difficulties in my field, he was always there to guide me and provide valuable advice and support (he always emphasised to me: Firgures are important in your work). I am especially thankful for the academic freedom he granted me, allowing me to explore my own research interests and methodologies. In life, he often took me to have a good chat at the beer hall in front of the school, sharing with us all kinds of interesting Belgian beers and other cultures, which made me feel like chatting with old friends even when I was alone in a foreign country.

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optimism and childish enthusiasm. With the encouragement, determination and hope, I was able and will continue to get off the ground and get things done.

Humanity is destined to be expelled from comfort, compelled to adapt to new lives; much like the animals migrating across the East African Plateau, we quietly part ways with those we've come to know, in search of the next silent goodbye. For many, life is but an absurd journey, an inexplicable meeting, knowing, and parting of souls, ending in connection or solitude. This realm of uncertainty ushers in new faces and freshness, spurring growth yet leaving us bewildered. A friend gently reminded me: Nietzsche once proclaimed, "Life is a splendid deception." Yet, I choose to believe in Proust’s wisdom: "Life is merely a series of isolated moments, strung together by memory and fantasy, revealing and concealing meanings like a series of waves leaping in the ocean."

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Yuqiao Long

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Chapter 1

General Introduction

1. Background

1.1. Importance for sustainable development goals

Since the World Food Summit (WFS) in 1996, notable advancements have been made in agricultural food production and security. This period marks a important turning point in agro-food dynamics (Ericksen, 2008; FAO, 2017). These advancements, however, are increasingly challenged by global changes that impact our ability to sustain and enhance these gains. The food production is essential for achieving Zero Hunger (SDG 2) within the broader 17 Sustainable Development Goals (SDGs). However, food security is confronted with a multitude of challenges, including population growth, urbanization, and climate change impacts (Abd-Elmabod et al., 2020; IPCC, 2014; Popp et al., 2014; Tilman et al., 2011; Tomlinson, 2013). Concurrently, the growing demand for agricultural products is leading to a greater need for cropland, which in turn is accelerating the degradation of land and the depletion of resources, and is endangering the ecosystem services that agricultural land provides (Eitelberg et al., 2015; Gutierrez-Arellano and Mulligan, 2018).

Cropland provides essential agricultural production including food, fuel, and fiber production (Scown et al., 2019; Stephens et al., 2018). In addition to agricultural production, cropland in the region provides a multitude of other valuable ecosystem services. For instance, in terms of regulating services, cropland soil management practices such as fertilizer application, diversified crop rotations, cover cropping, and reduced tillage practices to increase carbon storage have been widely discussed over the past two decades (Rumpel et al., 2018). Cropland affects the soil and water and regulates pests and diseases (Gutierrez-Arellano and Mulligan, 2018; Rabin et al., 2020). Cropland also provides habitat for wildlife and affects biodiversity (Byrd et al., 2015; Ricketts et al., 2004). Furthermore, cropland landscapes provide aesthetic value and recreation opportunities for local residents (Van Berkel and Verburg, 2014).

However, it is important to note that expanding cropland can conflict with certain ecosystem services (e.g. climate regulation through C storage, biodiversity, erosion protection) (Molotoks et al., 2018). Hence the need to expand cropland must be balanced with the delivery of these ecosystem services, necessitating innovations in technology and management practices to mitigate adverse impacts. Mitigating these potential impacts requires significant investment in technology, advanced data collection methods (such as remote sensing), and interdisciplinary research to improve cropland management (Gomes et al., 2021; Pereira et al., 2018). Such research endeavors will refine agricultural land management, thus bolstering food security and contributing to poverty reduction, health improvements. Given the global interconnectedness of food security challenges, the application of advanced land management practices, particularly in agriculturally intensive countries like

China, is essential for developing sustainable agricultural systems worldwide (Avtar et al., 2020; Wu et al., 2014a).

Considering the global agricultural challenges previously discussed, China represents a unique scenario with its vast population and substantial agricultural demands. Although it occupies only about 7% of the world's cropland, China supports nearly 20% of the global population (Lanz et al., 2017). This unique position underscores China's important role in addressing global food security challenges, making its land-use policies of global interest. Rapid urbanization in China has reshaped land-use patterns, causing a substantial reduction in cropland, especially in traditional agricultural areas such as the Yangtze River basin (Cui et al., 2019; Fang et al., 2021; Li, 2019; Tu et al., 2021; Xu et al., 2017a). This shift towards non-agricultural uses highlights the difficulty in balancing urban development with agricultural requirements, reflecting worldwide concerns about sustainable land use. Additionally, efforts to convert cropland to forests or grasslands in central areas for ecological restoration indicate a broader move towards sustainability and highlight the complexity of land-use decisions amid global food security challenges (Ma et al., 2013). Changes in China's agricultural landscape, documented since the 1980s, show significant spatial and temporal variations, contributing to the global discussion on sustainable food production (Liu et al., 2014a).

Changes in the distribution of cropland greatly influencing the national food production patterns (Pan et al., 2021; Yan et al., 2009). Traditionally, China's food production has been concentrated in the south (Shi et al., 2017). However, recent shifts suggest a transition towards a northward trend due to factors like urbanization, ecological restoration projects and temperature (Hu et al., 2019; Wang et al., 2018b). The Yangtze River Basin, which accounts for approximately 32% of the national grain production, is recognized as one of primary grain-producing regions (Hu, 2008; Ren et al., 2020b). The reduction of cropland in the eastern and central provinces, coupled with the expansion of cropland in the northern regions, has reduced the Yangtze River Basin's significance as a main grain-producing area (Zhong et al., 2022). Furthermore, the growing demand for dairy products has led to increased soybean imports and changes in crop structure, further impacting cropland area and grain production in China (Zhu et al., 2023). A crisis in cropland security within China's main grain-producing regions could potentially trigger a global food crisis (Ghose, 2014; Zhao et al., 2021a).

As agricultural transformations continue, the role of croplands now extends well beyond food production to include critical environmental functions, such as climate change mitigation through carbon sequestration. Concurrently with discussions on cropland distribution and grain production, the significance of croplands in the global carbon cycle and their potential to mitigate climate change has gained increasing recognition. The anticipated increase in global average surface temperature by 1.5°C between 2030 and 2050, largely due to significant carbon emissions, highlights the urgency to develop effective carbon sequestration strategies (Arneth et al., 2019; Kummu et al., 2021). In this context, the organic carbon content of croplands emerges as a crucial element in both reducing greenhouse gas emissions and enhancing food security (Lal, 2004; Paustian et al., 2016). However, the global expansion of croplands has also resulted in a significant loss of carbon from the soil, adversely impacting both agricultural productivity and climate dynamics (Liu et al., 2019; Tang et al., 2020). This highlights the need for a delicate balance between maintaining agricultural productivity and advancing ecological restoration, as emphasized by the increasing focus on nature-based carbon sequestration solutions (Bell et al., 2020; Bossio et al., 2020). Adopting such approaches is essential in managing the inherent trade-offs in agriculture's dual role as both a contributor to and a potential mitigator of climate change (Finch et al., 2023; Zheng et al., 2023).

Cropland abandonment is becoming a significant global issue parallel to the agricultural and environmental challenges faced by China, representing a critical aspect of land-use change with major implications for food security, biodiversity, and climate objectives (Huang et al., 2020; Næss et al., 2021; Potapov et al., 2022; Prishchepov et al., 2021b; Queiroz et al., 2014). This phenomenon has captured the attention of governments and the academic community worldwide, sparking extensive research and yielding significant findings (Prishchepov et al., 2021b). Cropland abandonment is a complex land use change process and has become a focal point of research across disciplines such as geography, economics, and ecology (Prishchepov et al., 2021b). The recognized importance of land management for climate change mitigation efforts, alongside increasing demand for land resources, provides opportunities for the abandonment of cropland and the consequent natural vegetation succession to significantly mitigate climate change (Fayet and Verburg, 2023; Gvein et al., 2023). Simultaneously, the reduction in cropland areas affects agricultural production, altering the availability of agricultural products and services, which is a great threat to China. Recognizing the equal importance and tradeoffs of ecological sustainability and food security, a deeper interdisciplinary understanding of cropland abandonment and its impacts is crucial for both scientific advancement and practical application.

Research on the driving factors of abandoned cropland has become an important topic. Geist and Lambin (2002) proposed that socio-economic, environmental and policy factors jointly drive abandoned cropland. emphasized that socio-economic factors are the main driving factors, and urbanization and industrialization lead to the outflow of rural labor and the abandonment of low-quality farmland (Raj Khanal and Watanabe, 2006). Wars and conflicts also play an important role (Yin et al., 2019). Environmental factors such as topography, soil characteristics, climate and water resources also affect the abandonment of cultivated land (Chaudhary et al., 2020). Policy factors, such as the Common Agricultural Policy of the European Union and access to credit, are also important (Pointereau et al., 2008). However, due to the complexity of the factors that lead to land abandonment, it is necessary to systematically understand their spatiotemporal evolution.

1.2. Remote sensing provides time-saving method for cropland monitoring

Remote sensing is a crucial tool in agricultural monitoring, primarily used for mapping agro-ecological landscapes. Although global mapping initiatives like ESA-CCI Land Cover and Globeland30 provide valuable insights, they often find it challenging to capture the complex nature of agricultural lands. This limitation has led to efforts of mapping specific crops and cropping practices with greater accuracy (Bégué et al., 2018; Bontemps et al., 2013; Chen et al., 2017; Fritz et al., 2015; Waldner et al., 2016). One of the key challenges in this area is acquiring high-resolution, frequent, and spectrally diverse data which is essential for accurate monitoring of land use. The latter is especially important when considering heterogeneous landscapes, e.g. dominated by smallholder farms (Burke and Lobell, 2017; Defourny et al., 2019). Advances in remote sensing technology, such as the Sentinel-2 constellation and cloud computing, have markedly improved the mapping of detailed land types. These advancements are crucial for monitoring changes in agricultural land use triggered by climate change and shifts in farming practices (Azzari et al., 2017; Gorelick et al., 2017; Ramankutty et al., 2002). Such detailed and timely information is increasingly vital for policymakers and regional decision-makers to manage evolving agro-ecosystems effectively.

1.3. Assessing ecosystem services using InVEST model

InVEST® (Integrated Valuation of Ecosystem Services and Tradeoffs, https://naturalcapitalproject.stanford.edu/software/invest) is an open-source geographic information system (GIS) software suite designed to map and assess diverse ecosystem services essential for sustaining human life. These services include the provision of goods (e.g., food crops), life-support functions (e.g., water purification), life-enhancing amenities (e.g., aesthetic landscapes and recreational opportunities), and the preservation of future potentials (e.g., genetic diversity conservation). InVEST enables decision-makers to quantify and evaluate the trade-offs associated with alternative management scenarios.

The toolset comprises multiple distinct models tailored to different ecosystem types, such as terrestrial, freshwater, marine, and coastal ecosystems. It also includes auxiliary tools for acquiring and processing input data, as well as for visually presenting and interpreting model outputs. The InVEST model is spatially explicit, with both inputs and outputs in the form of geographic spatial data. Model results can be expressed as biophysical metrics (e.g., carbon sequestration quantities) or economic values (e.g., net present value of carbon sequestration). The spatial resolution of analyses is flexible, allowing for application at local, regional, or global scales.

Several research groups from across the globe used the Carbon Sequestration module (C-module) in InVEST to assess the terrestrial carbon dynamic (Babbar et al., 2021; Fekadu Hailu et al., 2021; Pechanec et al., 2018). Previous studies have shown that this model is useful in estimating the carbon storage and sequestration because it can provide the relatively accurate simulation with the feasible and low demand for input parameters (Grafius et al., 2016; Jiang et al., 2017; Nelson et al., 2010). The C-module is an empirical, spatially explicit tool designed for practical applications in carbon storage and sequestration. It effectively balances complexity and usability, providing scientifically credible assessments of ecosystem services without requiring highly detailed biophysical process modeling. Although the C-module does not fully capture detailed carbon processes, its spatially explicit nature is crucial for understanding how different land uses impact ecosystem services within specific areas.

2. Problem statement

Despite the crucial role of China's agricultural sector in global food security, there is a significant gap in understanding the dynamics of crop production, particularly in critical regions such as the Yangtze River Basin where this knowledge is essential. Detailed research on cropland abandonment and recultivation is lacking, particularly in terms of spatial distribution and assessing ecosystem services, including food security and climate regulation. Moreover, the complex interaction between these two ecosystem services involves a critical trade-off mechanism that have not been fully explored. Obtaining a better ynderstanding of this trade-off is essential for developing policies that can effectively balance these competing priorities.

This thesis uses a multidisciplinary approach to analyze how different cropland patterns, including cropland intensification and large-scale utilization, drive food production. Cropland intensification refers to maximizing output through advanced techniques, fertilizers, pesticides, and capital, represented by the yield and Multiple Cropping Index (MCI). Large-scale utilization refers to extensive use of large cropland areas, quantified by the Number of Parcels (NP) and Mean Parcel Size (MPS). The present research also investigates the dynamics of cropland abandonment and recultivation in main production areas under high land-use pressure. It further explores the impacts of these cropland patterns on essential ecosystem services like food security and climate change mitigation, assessing the trade-offs and synergies among them. Initial findings suggest that the increase in China’s grain production can be attributed to factors such as global warming, recultivation of marginal lands, technological advancements, and shifts in cropping structures. Specifically, the recultivation of marginal lands, combined with cropland intensification techniques such as intercropping and relay cropping, has significantly boosted grain output by enhancing yield and efficiency (Jin et al., 2012; Li et al., 2009; Meyfroidt et al., 2016; Wezel et al., 2014; Xu et al., 2020). Industrial shifts towards more lucrative cash crops like cotton and oilseeds have negatively impacted food crop production, despite the intention to increase farmer incomes (Liu et al., 2018; Yuan et al., 2005). Additionally, climate warming has emerged as a significant factor positively influencing grain production (Fei et al., 2020; Liu et al., 2010). The influence of these factors on grain production growth varies across China, and their spatial distribution is not well understood. To address these complexities, our research will use both qualitative and quantitative methods, including remote sensing and statistical analysis, to map the spatial distribution of these factors and assess their impacts on grain production and ecosystem services throughout China.

Consistent mapping of cropland abandonment remains a major challenge in agricultural monitoring. Organizations like the FAO provide valuable annual statistics on active cropland at regional, national, and subnational levels through FAOSTAT. However, this aggregated data often fails to capture the complex spatial patterns or the detailed processes of changes, including both abandonment and expansion. Research concerning cropland abandonment primarily aims to understand its spatial and temporal patterns, including the extent, duration, and regional variations. This research uses methods such as sample surveys and remote sensing techniques. Sample surveys, including regional household surveys, are instrumental in revealing the socio-economic drivers behind cropland abandonment but often fall short in capturing spatial characteristics due to the subjectivity of the data (Zhang et al., 2023b; Zhang et al., 2014).

Remote sensing technology has been widely used in abandoned cropland (AC) monitoring due to its cost-effectiveness, efficiency, and accuracy (Alcantara et al., 2012; Yin et al., 2020). The main methods for identifying cropland abandonment include spectral feature comparison, trajectory-based approaches, and land cover classification-based approaches. Each method has its advantages and limitations. The spectral feature comparison method is simple but suffers from precision issues (Guo and Gong, 2018; Xu et al., 2018). The trajectory-based method can make full use of the spectral information of multi-year long time series to monitor the target features, mitigating the interference of abrupt changes due to noise. However, it is limited to monitoring the decrease or increase of a single object and fails to capture the conversion of the monitored object with other land cover types (Zhu and Woodcock, 2014). The land cover classification-based method though simple and generally applicable, is susceptible to error accumulation in long-term land cover change detection, impacting the detection accuracy (Du et al., 2021; Zhao et al., 2023). Cropland abandonment, a complex change detection problem, requires continuous monitoring and intricate land cover information, posing substantial challenges. Therefore, developing robust algorithms for cropland abandonment identification remains a key research focus.

Cropland abandonment can lead to significant ecological and environmental impacts, including alterations in landscape and biodiversity, changes in carbon storage, soil erosion and restoration, and increased wildfire risks. One notable consequence is the effect on terrestrial carbon sinks. As the duration of land abandonment increases, both vegetation cover and biomass typically rise at these sites. Kuemmerle et al. (2011) and Deng et al. (2014) demonstrated the carbon sequestration potential following cropland abandonment and conversion to grassland or forests. However, extensive cropland abandonment also risks significant losses in food production, potentially threatening food security. Research in main grain-producing nations and war-conflict regions has explored the impacts of abandonment on food production (Buchner et al., 2022; Guo et al., 2023; Jiang et al., 2023; Olsen et al., 2021; Yin et al., 2019). Although cropland abandonment poses threats to food security, recent studies and projects have shown it is feasible to restore them to natural landscapes to enhance carbon sequestration. However, such feasibility analyses require evaluating the trade-offs and synergies between various uses of abandoned cropland.

Given the evolving dynamics of cropland use and the critical role of ecosystem services, the investigation of trade-offs and synergies has recently emerged as a crucial focus in ecosystem services research (Qiu et al., 2018; Zheng et al., 2016), spanning multiple spatial scales (Bai et al., 2020; Howe et al., 2014; Jaligot et al., 2019; Jopke et al., 2015; Kusi et al., 2020; Shen et al., 2020b; Xu et al., 2017b) and employing various research methods (Lin et al., 2018; Morán-Ordóñez et al., 2020; Ndong et al., 2021; Sylla et al., 2020; Zhao et al., 2018). Recent studies highlight a gap in understanding how abandoned cropland can support both climate change mitigation and food security, lacking assessment on the trade-offs and synergistic effects among various ecosystem services (Dade et al., 2019; Qiu et al., 2021; Rimal et al., 2019; Zhong et al., 2020). This complexity is exemplified in the trade-off between carbon sequestration and grain production, illustrating the need to balance ecological benefits with agricultural productivity. Understanding the spatial variability in the duration of cropland abandonment is critical to assessing its influence on the current climate change and food crisis (Daskalova and Kamp, 2023). A key challenge is scale consistency, as food production and carbon sequestration are often discussed at different scales, making it difficult to effectively quantify trade-offs and synergies (Peng et al., 2017). Addressing this challenge requires research that incorporates both spatiotemporal scales and focuses on optimizing benefits at finer levels (Tilman et al., 2011). Given these complexities, there is an urgent need for more targeted research on abandoned cropland ecosystem services and better quantification and optimization of trade-offs and synergies in abandoned cropland management strategy.

3. Research objectives

The main objective of this thesis is to provide a comprehensive understanding of the essential need to manage cropland use changes. This management is crucial for achieving the United Nations Sustainable Development Goals (SDGs) in food-producing regions such as the Yangtze River Basin. The first specific objective is to assess the opportunities and constraints of the driving forces behind grain production changes in China from 2000 to 2010. This assessment will allow us, for the first time, to map the drivers of increased grain production at the county scale. The second objective focuses on challenges that threaten the sustainability of these gains, including cropland abandonment and the potential for recultivation. It aims to reveal the spatial and temporal dynamics of these processes in main grain-producing regions, particularly the Yangtze River Basin. The third objective examines the key environmental and societal benefits and trade-offs of cropland abandonment and recultivation. It uses spatial land use data derived from the analysis conducted in the second objective. Specifically, the following questions were formulated:

- What was the contribution of cropland intensification and large-scale utilization to increased grain production in China between 2000 and 2010?
- What are the spatial and temporal patterns of cropland abandonment and recultivation in main grain-producing regions during the period of 2000-2020?
- What is the impact of abandonment and recultivation on food security and climate change mitigation in the region?
- What are the trade-offs and synergies between food security and climate change mitigation in terms of their spatiotemporal patterns?

4. Structure of the thesis

4.1. Overview of the Thesis Structure

This thesis comprises five chapters, deriving from three peer-reviewed papers (two published and one in preparation), which explore the spatial-temporal dynamics of cropland and their impact on food security and climate change mitigation in China's primary grain-producing regions. As illustrated in Figure 1-1, the core of this thesis (Chapters 2-4) addresses each of the research questions directly.

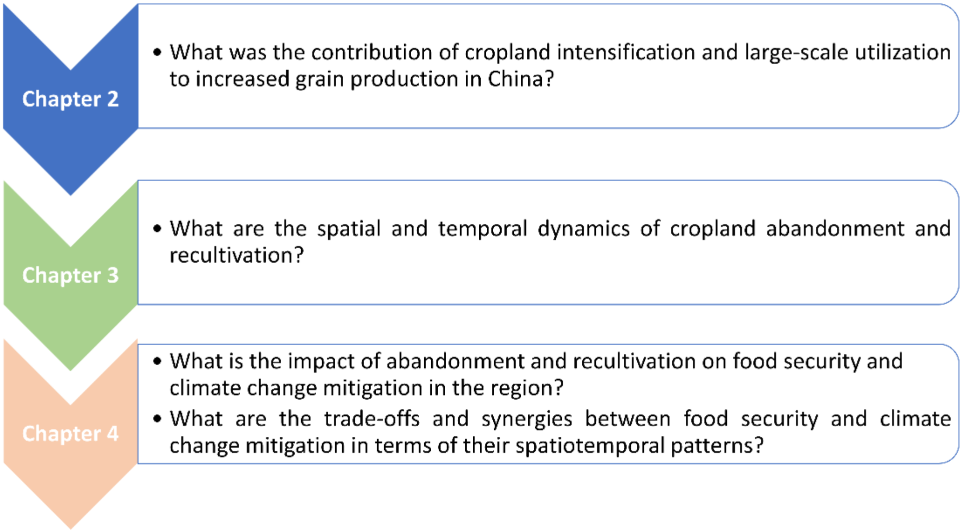

Figure 1-1. Thesis research questions and chapter contributions. The vertical V-chart indicates which chapter primarily addresses which research question (RQ). The first research question, on the assessment of food growth drivers, is mainly answered by Chapter 2. The second research question, on the distribution of spatial and temporal dynamics of cropland abandonment, is mainly answered by Chapter 3. Chapter 4 mainly answers two questions concerning of assessment ecosystem services and trade-offs and synergies. The key questions addressed are indicated next to the chapter numbers.

4.2. Chapter-by-Chapter Breakdown

Chapter 1 provides an overview of the thesis, introducing the background, problem statement, research objectives, and structure.

Chapter 2 assesses how cropland intensification and large-scale utilization contribute to crop production dynamics across China. It uses the Logarithmic-Mean-Divisia-Index (LMDI) method, alongside statistical and GlobeLand30 land cover data. This chapter aims to analyze various factors driving crop production increases, including yield, Multiple Cropping Index, Mean Parcel Size, and Number of Parcels. It seeks to highlight regional disparities and propose strategies for sustainably meeting national crop demand.

Chapter 3 explores the spatial and temporal dynamics of cropland abandonment and recultivation across the Yangtze River Basin (2000-2020), using MODIS time series and various land cover datasets. The focus is on uncovering the patterns and rates of cropland changes, with a special emphasis on widespread abandonment and the efforts towards recultivation. This analysis aims to deepen understanding of agricultural system evolution in a crucial region for China's food security, offering new methodologies for researchers and insights for policymakers to promote sustainable land use management.

Chapter 4 estimates the impacts of abandoned cropland in the Yangtze River Basin to food security and climate change mitigation. The chapter assesses trade-offs and synergies between climate change mitigation and food security, offering insights into optimizing landscape management and policy to enhance ecosystem services. This study aims to build on and complement the findings of Chapter 3 by deepening the understanding of the environmental and agricultural consequences of land use dynamics.

Chapter 5 summarizes the thesis findings, discussing the research outcomes, policy implications, limitations, and future research recommendations.

Chapter 2

Drivers of Grain Production Increases via Land Use Practice

This chapter is based on:
Long, Y., Wu, W., Wellens, J., Colinet, G., & Meersmans, J. (2022). An In-Depth Assessment of the Drivers Changing China's Crop Production Using an LMDI Decomposition Approach. Remote Sensing, 14(24), 6399.

Abstract

Over the last decades, growing crop production across China has had far-reaching consequences for both the environment and human welfare. One of the emerging questions is "how to meet the growing food demand in China?" In essence, the consensus is that the best way forward would be to increase crop yield rather than further extend the current cropland area. However, assessing progress in crop production is challenging as it is driven by multiple factors. To date, there are no studies to determine how multiple factors affect the crop production increase, considering both cropland intensification (using yield and Multiple Cropping Index) and large-scale utilization (using Mean Parcel Size and Number of Parcels). Using the Logarithmic-Mean-Divisia-Index (LMDI) decomposition method combined with statistical data and land cover data (GlobeLand30), we assess the contribution of cropland intensification and large-scale utilization changes to crop production dynamics at the national and county scale. Despite a negative contribution from MPS (Mean Parcel Size, -25%), national crop production increased due to positive contributions from yield ($+77\%$), MCI (Multiple Cropping Index, $+27\%$), as well as NP (Number of Parcels, $+21\%$). This allowed China to meet the growing national crop demand. We further find that large differences across regions persist over time. For most counties, the increase in crop production is a consequence of improved yields. However, in the North China Plain, NP is another important factor leading to crop production improvement. On the other hand, regions witnessing a decrease in crop production (e.g., the southeast coastal area of China) were characterized by a remarkable decrease in yield and MCI. Our detailed analyses of crop production provide accurate estimates and therefore can guide policymakers in addressing food security issues. Specifically, besides stabilizing yield and maintaining the total NP, it would be advantageous for crop production to increase the Mean Parcel Size and MCI through land consolidation and financial assistance for land transfer and advanced agricultural infrastructure.

1. Introduction

Increases in crop production over the last half-century due to cropland expansion and technological advances (e.g., fertilizers, pesticides, irrigation, etc.) have had far-reaching consequences for human welfare and the environment (Blomqvist et al., 2020). However, cropland intensification has resulted in a large scale conversion of grassland areas into croplands, adversely affecting biodiversity (Brambilla et al., 2021; Chaplin-Kramer et al., 2015; Foley et al., 2005) and climate change (Ren et al., 2020a). Unfortunately, these threats will probably intensify as projections estimate an increase in crop demand by at least another 50% by 2050 (Tilman et al., 2011). These impacts are likely to be worse for developing countries with a large population, such as China.

China has achieved remarkable crop production growth over the first decade of the 21st century, with total production equal to 552 million tons in 2010 according to records from the Food and Agriculture Organization of the United Nations (FAO) (https://www.fao.org/faostat/en/#data, accessed on 1st February 2022). In particular, the continuous growth of crop production between 2003 and 2010 has been important in delivering one of the most essential ecosystem services, i.e., food security. However, it is expected that China's food demand will continue to rise in the coming decades, as the country is increasingly dependent on imported food and feed (Zhao et al., 2021a). Additionally, during this period some land use change and management issues affecting food supply have occurred, including natural disasters (Fu et al., 2022), decline of high-quality cropland (Shi et al., 2013), and cropland abandonment (Li et al., 2018). In order to provide theoretical support for agricultural policymaking, it is necessary to clarify the extent to which different factors are driving the change in China's crop production.

Since 1961, the "Green Revolution" associated with the introduction of new agricultural technologies and practices has greatly improved China's crop production. An increase of 385% has been seen despite the fact that the overall cropland area only expanded by 29% according to the Yearly Statistics Book of the National Bureau of Statistics of China (NBSC) and FAO (http://www.stats.gov.cn/tjsj/ (accessed on 14th December 2021) and https://www.fao.org/faostat/en/#data (accessed on 1st February 2022)). Crop production can be defined as the total output of crop yield per unit area per year multiplied by its area. Although this metric has been widely used to quantify changes in agricultural production, it needs to be recognized that a large set of factors may have an impact on production, including several factors that have remarkably different effects on farming practices and technological advancements, altering entire food production systems (Blomqvist et al., 2020).

In the literature, crop production across China has typically not been studied in a simultaneously comprehensive and systematic way due to complicated agricultural settings. First, a thorough understanding of the spatial-temporal dynamics of crop production is hampered by the fact that most studies so far have focused on individual factors in isolation, such as drip irrigation (Lam et al., 2013), consumption of agricultural chemicals (Liu et al., 2015; Wu et al., 2018), policy regimes (Duan et al., 2021; Wu et al., 2018), or have just analyzed crop production as a whole in which individual factors are lumped together (Liu et al., 2009). Second, in these studies the influencing factors of crop production are hierarchical, for example, Multiple Cropping Index, yield, Mean Parcel Size, and Number of Parcels have direct impacts on crop production, whereas the above factors (e.g., drip irrigation) have an indirect impact on crop production by affecting the four directly influencing factors (i.e., Multiple Cropping Index, yield, Mean Parcel Size, and Number of Parcels). Hence, by assigning all types of components at the same influencing level, and therefore neglecting the interaction of influencing factors among the different levels, it is not possible to identify the true drivers behind crop production (Zhou and Zheng, 2015). Third, until now the Logarithmic-Mean-Divisia-Index (LMDI) has mainly been studied at the national and provincial scale (Bandara and Cai, 2014; Li et al., 2016b; Li et al., 2016d; Liu et al., 2014b), which is not detailed enough to reveal the underlying driving factors often operating at a smaller spatial scale. In fact, counties are the fundamental units of crop production in China, because the drivers within a given province may vary significantly at the county level (Yang and Tong, 2011). Hence, obtaining an understanding of the spatio-temporal variability in crop production and its associated drivers at the county scale is crucial for the development of regional policies to combat food security issues and to address the associated United Nations Sustainable Development Goals (SDGs). Fourth, the lack of studies that cover the entire nation makes it difficult to make interregional comparisons. As a solution to these critical shortcomings, we introduce a framework that decomposes crop production into factors, which can all be quantified.

Structure Decomposition Analysis (SDA) and Index Decomposition Analysis (IDA) are two commonly used methods for the decomposition of indicator changes. The IDA methodology is easy to use because of its simplicity and flexibility, compared to the SDA method, therefore IDA has been extensively applied. IDA can be further divided into the Divisia Index Decomposition technique and Laspeyres Index Decomposition technique (Ang et al., 2009). We applied the Logarithmic-Mean-Divisia-Index method (LMDI), which has many advantages, including perfect decomposition (no residuals), zero-value robustness, time-reversal symmetry, and consistency in aggregation (Ang, 2004; Ang and Liu, 2001). The LMDI has been widely applied in industrial research focusing on energy efficiency and carbon dioxide emissions at the national scale (Akbostancı et al., 2011; Sun et al., 2012; Tan et al., 2011). However, to our knowledge, very few studies have utilized this decomposition methodology to unravel factors influencing crop production.

The first decomposition factor is yield, which is the output of a given crop per unit of harvested cropland area for a given location, typically expressed in tons/ha. The second factor is the Multiple Cropping Index (MCI), the average frequency at which crops are planted per year or accumulation of harvest area on a given unit of cropland area per year. Yield and MCI are both a clear indicator of cropland intensification, but they are nonetheless important to distinguish as they do not necessarily reflect the same aspects of crop production (Ray and Foley, 2013).

The next two factors are related to cropland large-scale utilization (Bonfanti et al., 1997; Shi et al., 2018). We consider two important landscape metrics, i.e., the Number of Parcels (NP) and Mean Parcel Size (MPS), in order to reflect how farmers cultivate as a function of cropland size, which indicates the degree of large-scale utilization at a given location. An increase in large-scale utilization can affect crop production in the sense that a shift toward lower farming costs could result in higher farming returns, and hence, higher crop production (Duan et al., 2021; Huang and Ding, 2016). Knowing how large-scale utilization changes is therefore critical to understanding its impact on ongoing food security issues. However, this critical research question has received little attention from researchers so far.

Hence, this study aims to: (1) decompose crop production into relative factors (yield, MCI, MPS, and NP) and map the change of each factor between 2000 and 2010 using GlobeLand30 and statistics data; (2) assess the contribution of yield, MCI, MPS, and NP to crop production changes at both the nation and county scale; and (3) map the spatial pattern of these contributions at the county scale and identify the dominant factors.

By applying a novel graphic information system (GIS) based approach, we were able to produce a detailed spatial-temporal analysis of how agriculture has met the rising food demand over the first decade of the 21st century.

2. Materials and Methods

2.1. Study Area

In this study, we consider all of China. The complex topography and, hence, wide range of climates has resulted in many different cropping systems throughout China (Figure 2-1). For example, in some parts of central China and northern China, only a single rice crop is grown each year because the growing season is too short for multiple crops, whereas in the south and some parts of central China, farmers practice a double rice cropping system (Deng et al., 2019). When considering hydrothermal conditions of the landscape, for the same crops and altitudes higher grain yields are obtained on slopes orientated towards the south compared to other aspects, because of warmer temperatures for these topographical positions. However, as a result of steep mountainous terrain, farmers cultivate land everywhere, which has led to considerable fragmentation of the cropland area, and therefore gradually decreased the average field size. This is phenomena is most remarkable in south China.

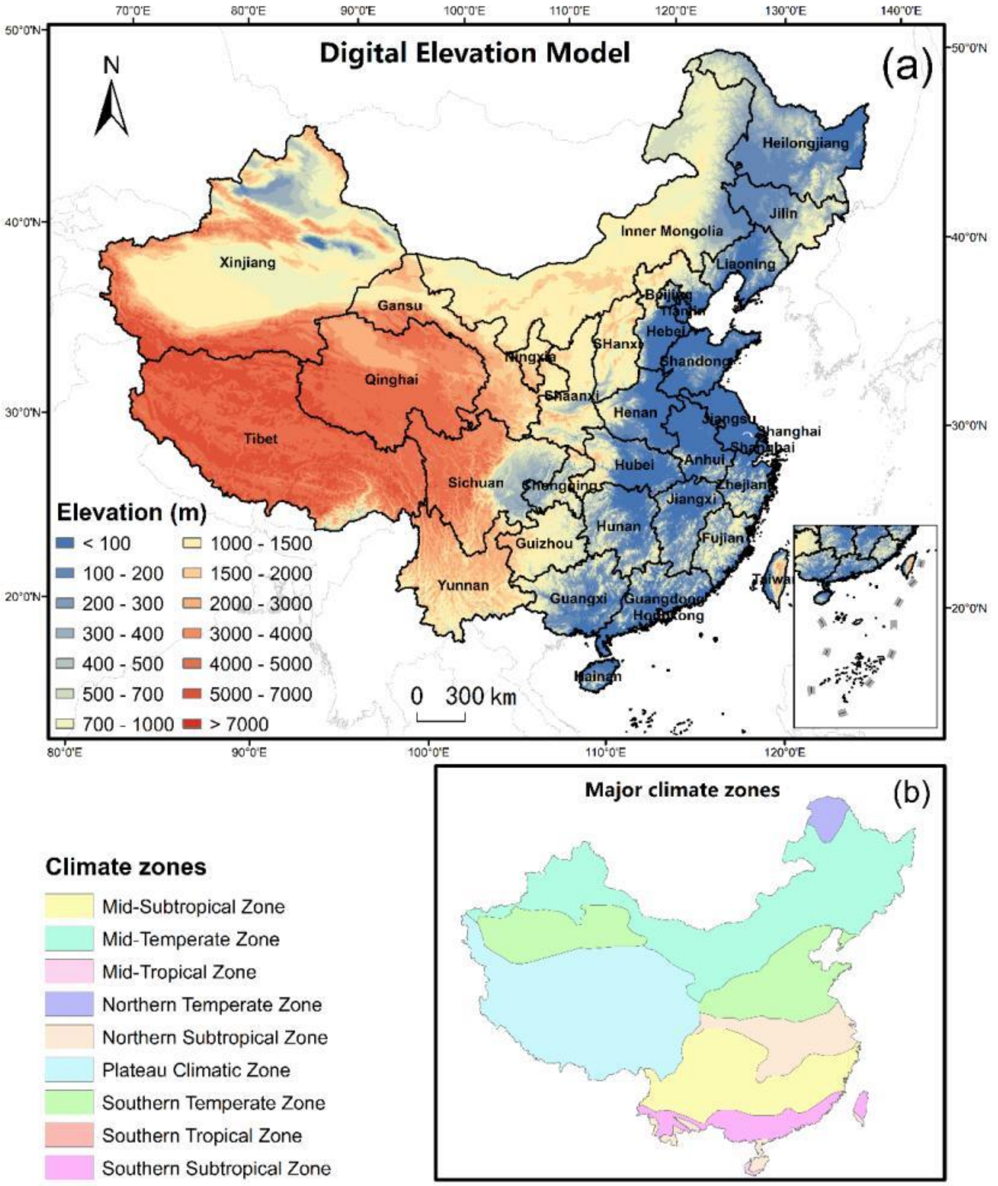

Figure 2-1. Digital elevation model and climate zones of China with annotation of the provinces.

2.2. Data Sources

An overview of the data used in this paper is shown in Table 2-1. Spatial and statistical data for 2000 and 2010 were collected. Our analysis included 2396 counties across China for which data on yield and MCI were available from the China County

Statistical Yearbook (NBSC, 2001 and 2011). The county administrative boundary was acquired from the Geographical Information Monitoring Cloud Platform (http://www.dsac.cn/, accessed on 1st December 2020). The administrative divisions of cities were adjusted during the studied periods. Consequently, the administrative boundaries for 2010 were adopted to make the county unit uniform in size. However, in this study, we did not consider Taiwan, Hong Kong, and Macao due to data unavailability. Data on agriculture was obtained from the NBS. To calculate yield and MCI, the total crop production and harvest area were collected from China Agricultural Statistical Yearbook. To reduce the impact of uncertainty in the census data, missing data were complemented using the three-year average data.

In our study, we used GlobeLand30 (Figure 2-2), which is the world’s first global land cover dataset at a resolution of 30 m (http://www.globallandcover.com, accessed on 1st December 2020). The GlobeLand30 dataset was extracted from more than 20,000 Landsat and Chinese HJ-1 satellite images and based on the integration of pixel- and object-based methods with knowledge (POK-based) (Chen et al., 2014; Chen et al., 2015). This product consists of 10 land cover types among which cropland was defined as the agricultural land use type, including dry land, paddy fields, artificial grasslands, tea plantations, greenhouses, fallow land, and even abandoned cropland (Cao et al., 2016). The overall accuracy of the GlobeLand30 derived cropland area across China is higher than 80% (Lu et al., 2016; Wang et al., 2018c; Yang et al., 2017). In addition, we found that the cropland area of GlobeLand30 is consistent with statistical data at the county scale (Supplementary information Figure S1). This relatively high spatial resolution and wide spatial coverage provides us with the opportunity to assess some key factors characterizing large-scale utilization, i.e., Number of Parcels (NP) and Mean Parcel Size (MPS) across China using the FRAGSTATS 4.2 software (McGarigal and Marks, 1995).

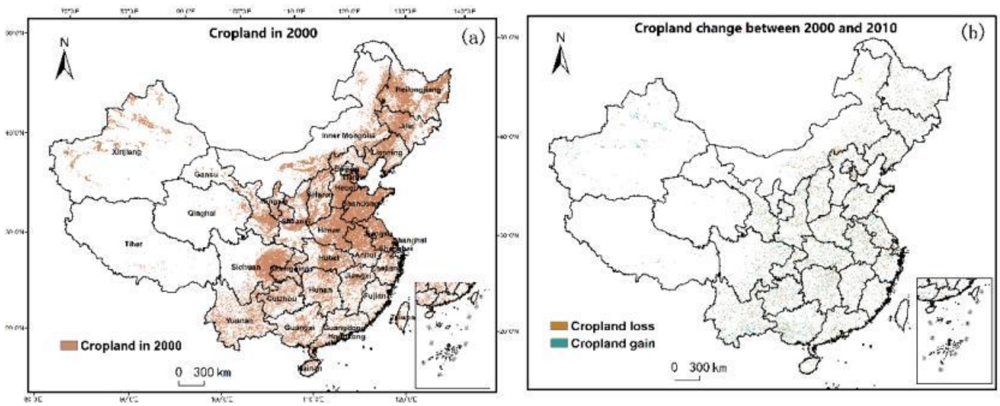

Figure 2-2. Spatial pattern of cropland in GlobeLand30 ((a): 2000, (b): 2000–2010). Note that the overall accuracy of GlobeLand30 in China has reached 80%, including the cropland layer. The maps were generated using ArcGIS 10.2 ESRI (Environmental Systems Research Institute, 2013).

Table 2-1. Data used in this paper.

Data Type	Year	Description	Data Sources
Agricultural data	2000, 2010	Crop production in each county	China County Statistical Yearbook, NBSC, 2001 and 2011
		Cropland harvest area in each county	
Land-use imagery	2000, 2010	GlobeLand30 land-cover dataset with 30 m spatial resolution across China	www.globallandcover.com
Auxiliary data	2010	County administrative boundary in China	http://www.dsac.cn/ (accessed on 1st December 2020)

2.3. Methods

2.3.1. Yield and MCI Estimation

Two significant indicators that are used to quantify the input and output of cropland in a detailed way are crop yield and MCI (Equations (1) and (2)), which are used to reflect the degree of cropland intensification.

$$yield = C_{total}/H \tag{1}$$

$$MCI = H/A \tag{2}$$

Where $yield$ (tons/ha) represents crop production level, C_{total} (tons) is the total crop production in a given region, H (ha) is the total harvest area in a given region, MCI represents crop production frequency, and A is total cropland area in a given region (ha).

2.3.2 MPS and NP Estimation

Landscape metrics are quantitative measures used to characterize landscape patterns. These metrics are used to establish associations between landscape patterns and landscape processes. In this study, we calculated two landscape metrics (i.e., NP and MPS) to assess the degree of large-scale utilization (see Table 2-1). To do so, we used FRAGSTATS 4.2 software, which allowed us to calculate these indicators directly from the spatial pattern of cropland. When large-scale utilization develops positively, the Number of Parcels may decrease whereas the Mean Parcel Size increases. This means that the spatial distribution of cropland becomes more concentrated. Hence, by using these indicators, we can evaluate the degree of large-scale utilization in each county and the entire nation considering the period 2000–2010.

2.3.3. LMDI Decomposition

To analyze the changes of crop production over a given period of time considering multiple factors, we adopted a LMDI analysis (Ang and Liu, 2001). As crop production in a certain region has been shown to be highly related to yield, MCI, and cropland area (A), we considered these factors in our analysis. Cropland area (A) was further divided into NP and MPS.

Our analysis is based on crop production in which C_{total} is the sum of crop production expressed in tonnes per year, which was calculated as follows:

$$C_{total} = \sum_{i=1}^{n} C_i \tag{3}$$

where C_i is the crop production of county i.

$$\begin{aligned} C_{total} &= \sum_{i=1}^{n} yield_i . MCI_i . A_i = \sum_{i=1}^{n} \frac{C_i}{H_i} . \frac{H_i}{A_i} . \frac{A_i}{NP} . NP \\ &= \sum_{i=1}^{n} yield_i . MCI_i . MPS_i . NP_i \end{aligned} \tag{4}$$

Subsequently, the C_{total} was disaggregated into four factors, i.e., yield ($yield_i = \frac{C_i}{H_i}, tons/ha$), MCI ($MCI_i = H_i/A_i$), MPS ($MPS_i = \frac{A_i}{NP}, ha$), and NP_i.

The LMDI was divided into additive decomposition and multiplicative decomposition. However, the two decomposition methods display similar results. Because the additive decomposition approach is easier to use and interpret compared to the multiplicative decomposition approach, the following additive decomposition was employed:

$$\Delta C_{total} = C^{T}{}_{total^i} - C^{t}{}_{total^i} = \Delta C_{yield^i} + \Delta C_{MCI^i} + \Delta C_{MPS^i} + \Delta C_{NP^i} \tag{5}$$

where $C^{T}{}_{total^i}$ and $C^{t}{}_{total^i}$ are the crop production in county i during the period T and t, respectively. ΔC_{yield^i} represents the contribution of yield to crop production changes in county i.

The degree to which each effect contributes to the change in the crop production of China's agriculture sector was estimated by the following equations. In this study, T = 2010 and t = 2000.

$$\Delta C_{X^i} \approx \sum_{i} L(C^{T}{}_i, C^{t}{}_i) . ln \frac{X_i^{\ T}}{X_i^{\ t}} \tag{6}$$

where $L(a, b) = (a - b)/(ln\ a\ -\ ln\ b)$ is the logarithmic mean, ΔC_{X^i} denotes the crop production contribution of each factor ($X : yield, MCI, MPS,$ and NP) in county i. The specific expression for each decomposition factor, given in LMDI form, is shown in Supplementary information Table. S1.

An overview of the entire methodological approach can be found in Figure 2-3.

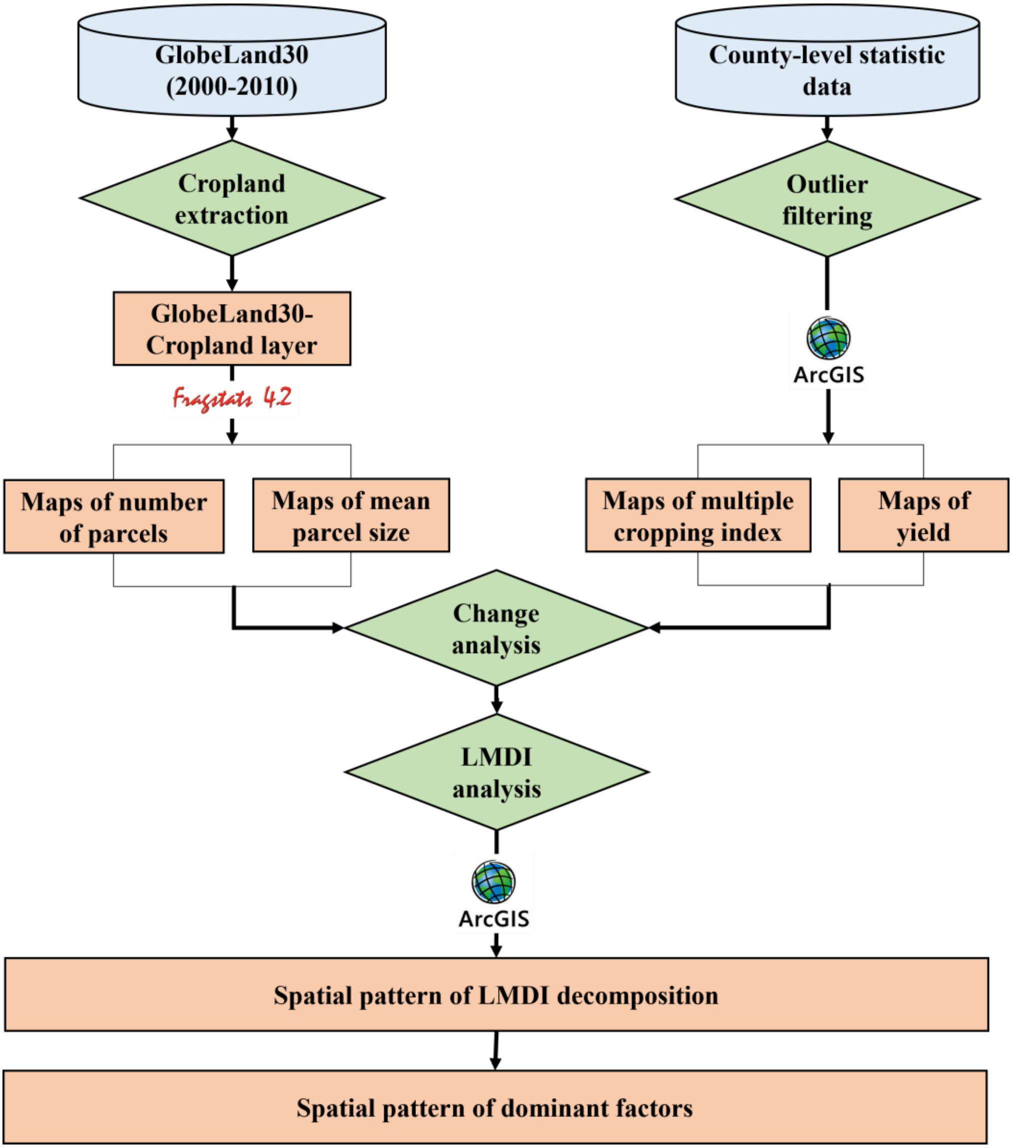

Figure 2-3. Flowchart of the methodological approach. Our study approach comprises the following steps: (1) Extracting cropland layer from GlobeLand30 and calculating landscape metrics using FRAGSTATS 4.2; (2) Calculating crop yield and Multiple Cropping Index at the county scale based on statistical data; (3) Quantifying the contributions of all four indicators to crop production change, including food, feed, and fiber crops (cylinders = datasets, diamonds = data-processing and method, rectangular = results and maps).

3. Results

3.1. Spatial Patterns of Yield, MCI, MPS, and NP

The results show that yield and MCI are characterized by an increasing trend in most counties (Figure 2-4). Increases in yield were most pronounced in the Yangtze River Basin, the North China Plain and the northeast of China, which are the major crop production regions and are dominated by crops, such as rice, corn, and soybean. Together these regions account for 69% of national food production (National Bureau of Statistics of China, NBSC). These regions were also characterized by an increase in MCI. However, yield and MCI decreased across the southeast of China (Figure 2-4). This was especially the case along the southeast coast (i.e., Guangdong province, Fujian province, and Zhejiang province). When looking to the county scale, this study indicates that 62% of the counties (1495 out of 2396 counties) were characterized by an increasing trend in yield, whereas 31% had a decreasing trend in yield. For MCI, 54% and 36% of counties were characterized by an increasing and decreasing trend, respectively.

The maps indicated an increasing trend in NP across most (61%) of the counties; for instance, there was a clear increasing trend in NP in the northern part of Inner Mongolia. Moreover, Jiangxi province and Zhejiang province were also characterized by an increasing NP. However, NP decreased in some counties in the central and southern part of China (e.g., in Hunan province and Guangxi province), indicating that agricultural parcels either became more fragmented or that cropland farming was disorganized. In contrast to NP, MPS was characterized by a general negative trend. More specifically, the results show a clear downward trend in MPS across the eastern part of China, which may be related to the conversion of croplands into other land cover types or a higher degree of landscape fragmentation.

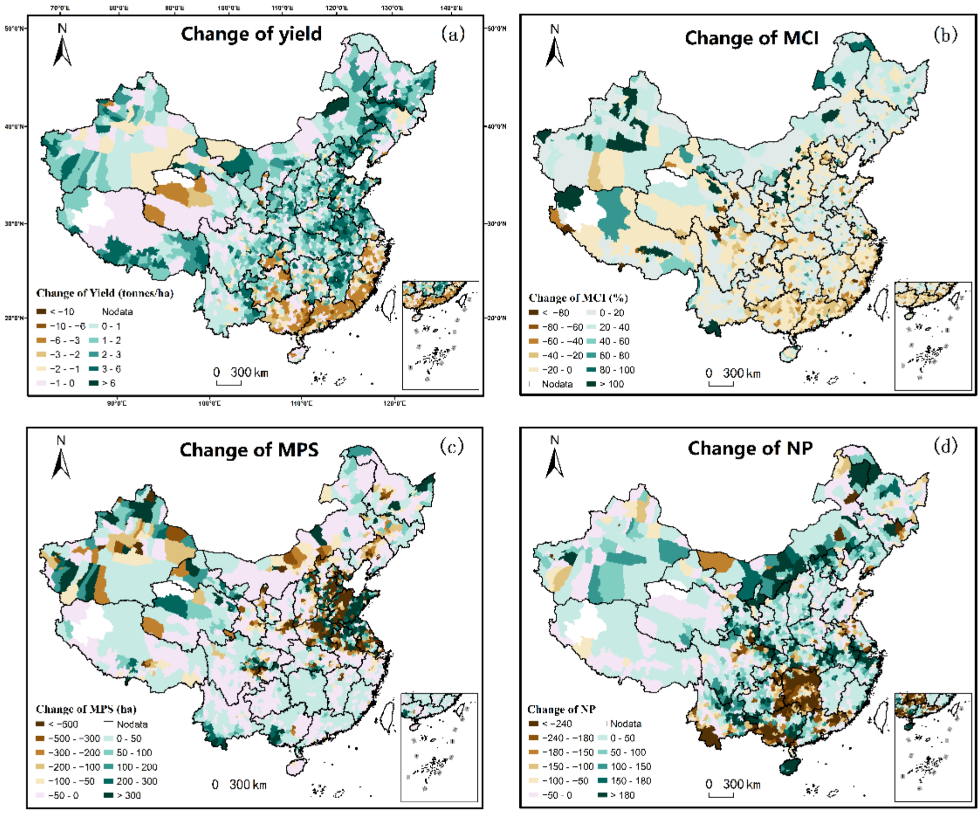

Figure 2-4. Characterization of change in four factors ((a): yield, (b): Multiple Cropping Index (MCI), (c): Mean Parcel Size (MPS), (d): Number of Parcels (NP)) at the county scale across China between 2000 and 2010.

3.2. Spatial Pattern of Crop Production Changes and National Decomposition

Since the 2000s, when China began to reinforce rural economic reform, crop production has been characterized by remarkable growth. This is reflected in the general increasing trend in crop production across the nation, as shown in Figure 2-5. Over the period 2000–2010, China's total crop production has increased by 30%. As our results indicate, more than 60% of the counties experienced an increase in crop production, which were mainly located in the northeast of China as well as across the North China Plain, also called "the breadbasket of China". A total of 70% of the area of these regions is characterized by flat topography (e.g., extensive plateaus or valleys), and therefore these are the predominate crop production areas making a significant contribution to national overall crop production growth. However, 29% of the counties across China were characterized by a loss in crop production, which were mainly located in southeast coastal regions, scattered across the Guangdong, Fujian, Zhejiang, and Guangxi provinces.

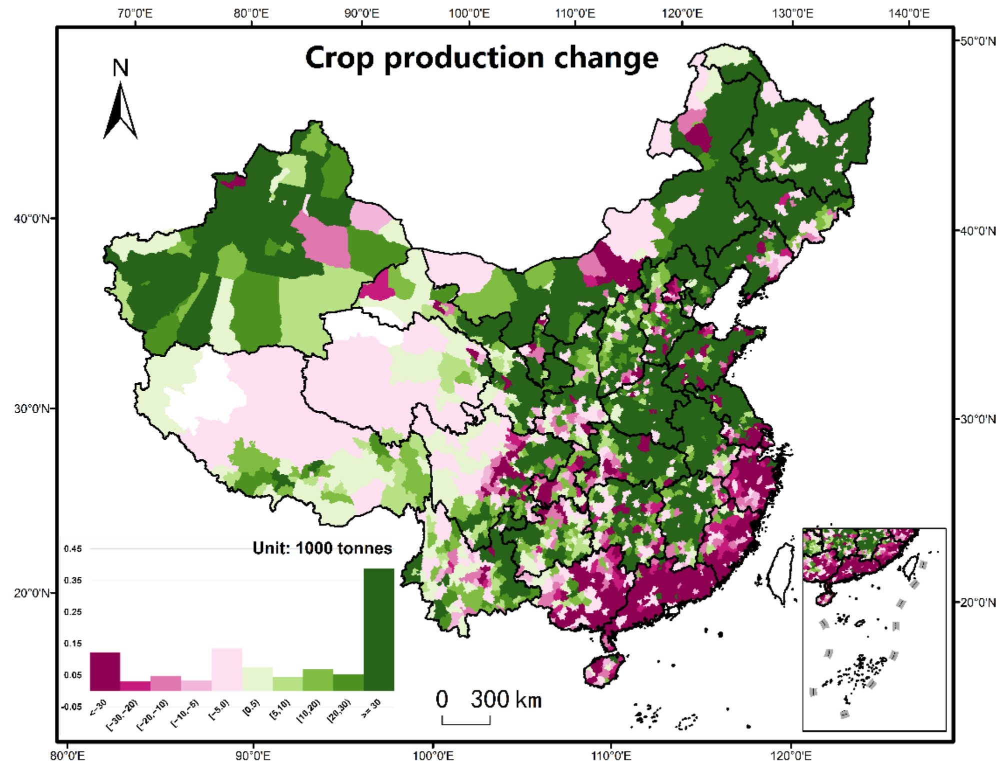

Figure 2-5. Map of crop production change at the county scale across China. The bar chart shows the proportion of the counties characterized by a given change in crop production corresponding to the intervals displayed in the legend of the map.

In the present study, the factor decomposition breaks the nationwide increase in crop production down into four contributing factors (i.e., yield, MCI, NP, and NPS). Figure 2-6 shows that the overall crop production increase in China has mainly been driven by three factors, i.e., MCI, yield, and NP, of which yield had the most important influence. More specifically, yield had a relative contribution of 77% to the total crop production change, whereas MCI and NP contributed only +27% and +21%, respectively. In contrast, MPS had a somewhat negative impact on crop production change, accounting for −25%.

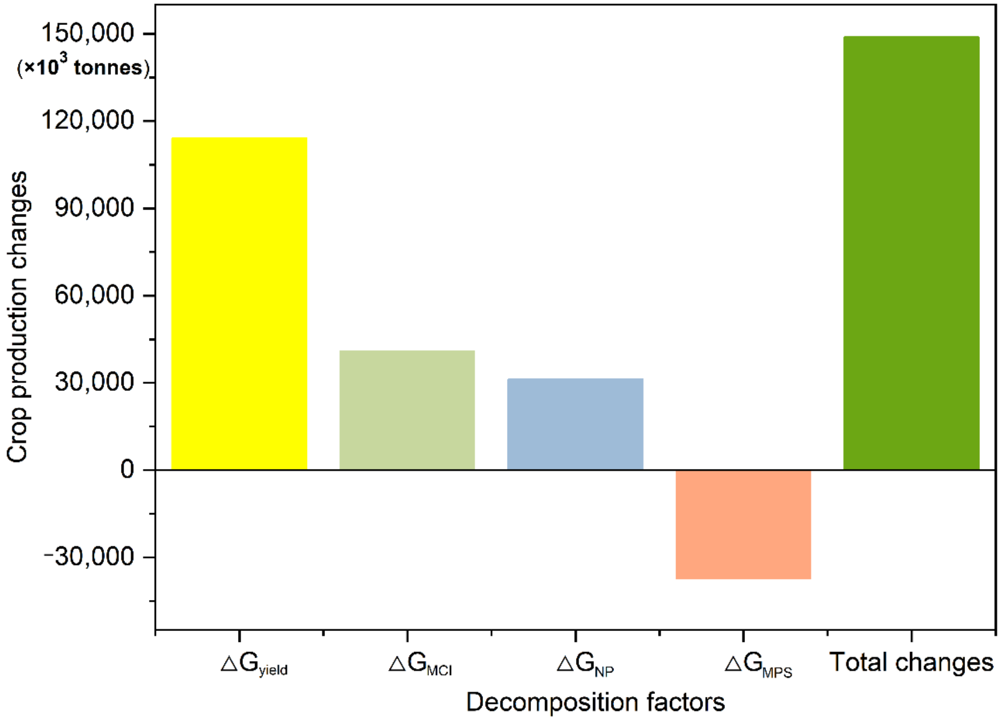

Figure 2-6. Factor decomposition of the total change in crop production across China between 2000 and 2010, considering the contributions of yield (ΔG_{yield}), Multiple Cropping Index (MCI, ΔG_{MCI}), Number of Parcels (NP, ΔG_{NP}), and Mean Parcel Size (MPS, ΔG_{MPS}).

3.3. County-Scale Decomposition

Figure 2-7 shows the county-scale decomposition map per factor (i.e., yield, MCI, MPS, and NP presented in the subpanels a-d, respectively) allowing us to obtain deeper insights into the spatial pattern of the various drivers changing China's crop production. This result shows that the increase in yield had a positive effect on crop production within 62% of the counties (1486 out of 2396 counties, Figure 2-7(a)). Among them, 43% of the counties (641 of these 1486 counties) have a contribution of more than 100,000 tons per county and 26% of more than 200,000 tons. These counties are mainly located across the major crop production regions (e.g., the North China Plain and the northeast of China). On the other hand, in 31% of counties (739 out of 2396 counties) yield had a negative influence on crop production; these are mainly located along the southeast coast of China and somewhat scattered in the west of China. However, among these 739 counties, less than 15% experienced a negative contribution of more than 100,000 tons, and most counties are restricted to a negative contribution of 50,000 tons.

The results indicate that MCI decomposition has a positive effect on crop production within 54% of the counties (Figure 2-7(b)). Among them, 67% of these counties have a contribution of less than 50,000 tons. The analysis shows that these counties were concentrated in the provinces of Yunnan, Guizhou, and Hunan. However, in 38% of the counties, MCI had a negative influence on crop production; these are mainly located in the southeast of China and the North China Plain. The majority of these counties characterized by a negative contribution of MCI to crop production are limited to 50,000 tons.

Furthermore, MPS had a positive effect on crop production in only 37% of the counties (Figure 2-7(c)). Counties characterized by a remarkably positive contribution of MPS to crop production are located in important cropping areas across China, including the Chengdu Plain, Hunan province, and Shandong province. However, crop pro-duction was negatively impacted by MPS in 53% of the counties, which posed a threat to local food security. Nearly a fifth of the counties are characterized by a reduction of more than 100,000 tons of crop production due to the negative impact of MPS; these are mainly located in the provinces of Henan, Shandong, and Anhui.

Crop production was positively influenced by NP in 52% of the counties (Figure 2-7(d)), which were mainly located in the North China Plain, including Hebei province, Shanxi province, the Loess Plateau, and the southwest of China. This effect is limited, with 70% of counties having a contribution of less than 50,000 tons. However, some counties in Hunan province, the south of Yunnan, and the north of Jiangsu experienced a rather strong negative contribution of NP to crop production. In these counties, the overall negative contribution of NP to crop production is as great as 6311 $\times 10^4$ tons, which should be considered as a substantial offsetting of the total NP-induced crop production increase (i.e. 3116×10^4 tons), as shown in Figure 2-6.

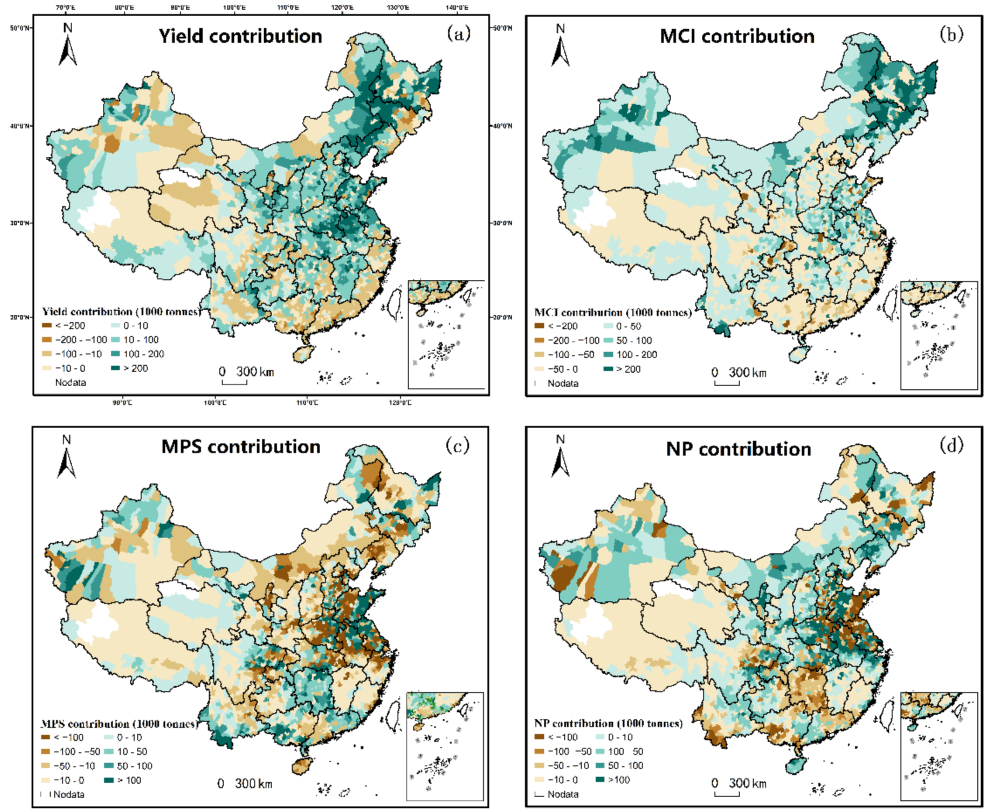

Figure 2-7. Decomposition of crop production change across the China at the county scale with the individual contributions of the factors being given in the subpanels, (a): Yield, (b): Multiple Cropping Index (MCI), (c): Mean Parcel Size (MPS), (d): Number of Parcels (NP).

3.4. Identification of Dominant Factors

Comparing the decomposition analyses of the different factors could facilitate our understanding of the mechanism behind the observed changes in food provision at the national scale and provide us with useful information for policymaking. The map in Figure 2-8 presents the dominant factor influencing the crop production changes at the county level. This map also indicates whether there is a net increase (+) or decrease (−) in crop production. From this analysis we can see that in a large number of the counties where crop production increased, yield was the most dominant factor (i.e., 51% of the counties with increasing crop production), which were predominantly distributed across the northeast of China, in the provinces of Hebei, Shanxi, and Jiangxi. MCI was the second most dominant factor in counties characterized by increasing crop production. This accounted for 22% of these counties, mainly distributed across the northeast of China, such as Heilongjiang province. The proportion of counties characterized by an increase in cropland production in which

MPS and NP were the dominant factors was relatively small and scattered across the nation, i.e., 13% and 14%, respectively,

Conversely, when considering the counties characterized by a decrease in crop production, approximately 33% of them experienced a dominant MCI-based impact. This is especially the case for the counties located along the southeast coast of China in which a remarkable decline in MCI caused a decrease in crop production. In 28% of the counties characterized by a decrease in crop production, this was the result of lower yields, which were spatially scattered. However, when comparing regions with either a yield-based negative contribution or yield-based positive contribution, there is still a clear overall net positive effect of yield on overall crop production. The counties with MPS and NP as the dominant factors leading a decline in crop production are scattered across China, accounting for 24% and 15% of the counties characterized by decreasing crop production, respectively.

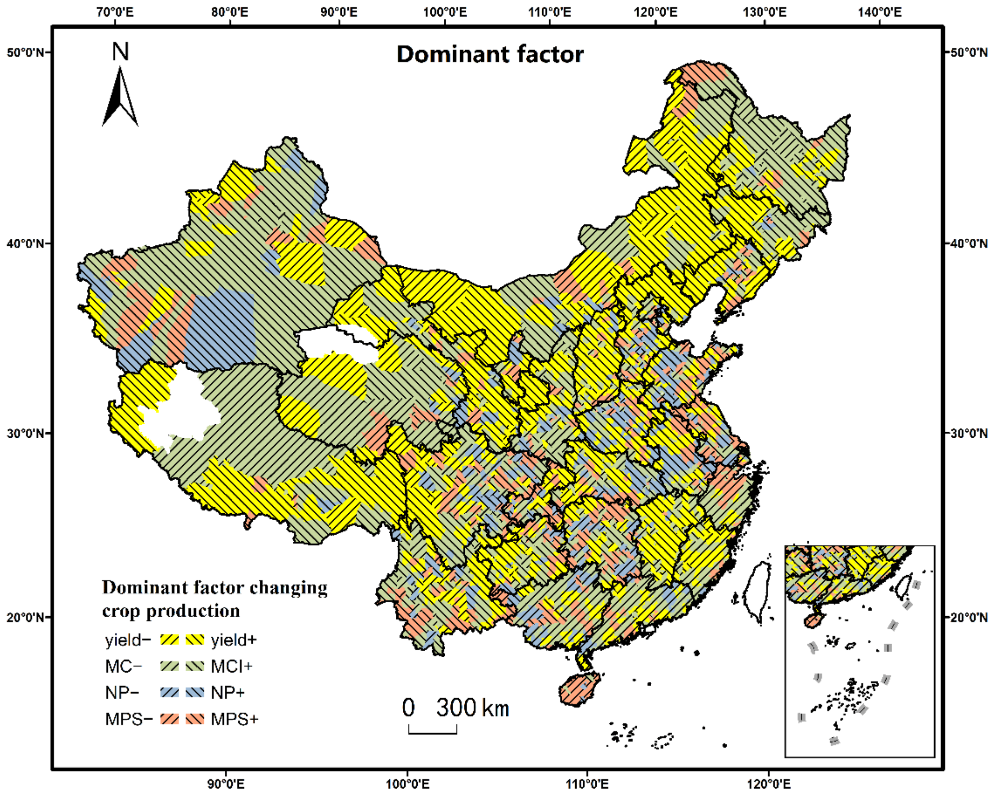

Figure 2-8. Spatial pattern of the dominant factors influencing crop production in China. Colors represent the dominant factor, whereas hatching indicates the overall crop production trend (i.e., "+" is net increase and "–" is net decrease in crop production).

4. Discussion

4.1. Crop Production Drivers

To our knowledge, this is the first attempt to conduct a detailed factor decomposition analysis of crop production in China at the county scale across the entire nation. In comparison with other studies investigating crop production trends, we found some similarities in terms of overall results but this study is characterized by some important methodological advances. For example, Li et al. (2016) decomposed grain production into yield, cropland area, and crop-mix at the (sub)national scale, whereas we were able to perform this research at the county scale (Li et al., 2016b). They found that China's grain output increase between 1998 and 2013 was mainly driven by yield (+72%), which is similar to our results (+77%). However, their analysis did not consider the effect of changes in MCI on grain production increase, which was shown to be a key factor in our study. Other studies also underline the wide-ranging impact of MCI on agricultural production (Licker et al., 2010; Neumann et al., 2010). Zhou et al. (2015) found that yield (+101%) and MCI (+81%) had a positive effect on grain production between 1992 and 2012 (Zhou and Zheng, 2015). However, this study is more limited than ours as it only analyses national scale changes due to the use of a coarse statistical dataset. In contrast, our novel approach decomposes the major factors influencing crop production change and enables the detection of more detailed spatial patterns at the county scale, which could be useful to support the development of regional crop policies.

To date, no studies have considered NP and MPS as contributors to crop production change. These factors seem to be key indicators for the degree of large-scale utilization (Cheng et al., 2015) and, hence, may determine land use patterns at the national/subnational scale. Consequently, we included these factors in our study. Our results suggest that area decomposition can provide a better understanding of how large-scale utilization may affect crop production, therefore we believe that these factors should be taken into consideration when providing policymakers with science-based advice. In essence, considering the four factors used in this study (i.e., yield, MCI, NP, MPS)—combinations of which comprehensively reflect the farming system—allows us to obtain substantially better insights into the mechanisms driving the observed crop production changes across China.

To our knowledge, few papers have rigorously quantified the effect of large-scale utilization operations on crop production (Duan et al., 2021; Zhu et al., 2018). In essence, these studies found that land consolidation or land transfer due to large-scale utilization increased the agricultural output (e.g., income). Although this can be seen as a significant conceptual and methodological advancement, our approach has some additional novelty because we applied the LMDI method instead of the typically used regression modeling approach.

4.2. Regional Diversity in cropland intensification and Large-Scale utilization

Our research showed that both yield and MCI increased at the national scale, which indicated significant agricultural development across China (Figure 2-6). However, the high variability in these factors highlights considerable regional differences. This result has been confirmed in previous studies based on remote sensing and statical data (Xie and Liu, 2015; Yan et al., 2019), explaining that the high variability could well be due to climate change. More precisely, climate change has altered the cropping pattern across China (Liu et al., 2013; Yin et al., 2016), with some land becoming degraded and other land that was previously unsuitable for farming being cultivated. For example, rice cropping has moved northwards (Ye et al., 2015). Furthermore, agricultural policies have helped farmers by encouraging farming incentives and revenues, which have contributed to the process of agricultural intensification (Zuo et al., 2014). However, the migration of young people from rural to urban areas may have resulted in a decline in yield and MCI (Xie and Jiang, 2016). This phenomenon is most present in the southern part of China (e.g., Chongqing municipality, Guizhou province, and Guangxi province). In the southeastern coastal areas (e.g., Guangdong province, Fujian province, and Zhejiang province) rapid urbanization has led to the conversion of vast cropland areas into artificial surfaces, which is probably the most important driver for yield and MCI decreases in these regions (Wang et al., 2012).

Additionally, we noticed an overall increase in NP and decrease in MPS, indicating that China is experiencing cropland fragmentation. This result was verified by previous studies (Fang et al., 2016; Yu et al., 2018), but the regional NP and MPS trends may diverge from those observed at the national scale. Furthermore, our findings indicate that the most important factor causing a decline in MPS across some counties in the North China Plain may be urbanization. This suggests that the current urbanization process may be sacrificing cropland and further fragmenting the larger cropland patches into smaller pieces (Xu et al., 2016). Furthermore, policy support and agricultural innovation have affected the degree of large-scale utilization, causing an increase in MPS. In the North China Plain, for example, MPS in some counties may have increased due to the land transfer policy, mechanization, and improved irrigation techniques. However, it should also be highlighted that some counties in the western and southern parts of China have been characterized by a general trend of agricultural land concentration due to the implementation of ecological restoration programs, e.g., the “Grain for Green” program, which have converted marginal cropland on sloping land into natural vegetation, decreasing the number of cropland patches (Wang et al., 2017).

4.3. Impact of Agricultural and Land Management Practices

When considering the overall increase in crop production, the shift towards crops characterized by higher-yield production seems to be an important driver (2016b; Pan et al., 2020). Previous studies have indicated that yield was the largest driving factor for rising agricultural production across China between 1961 and 2009 (Zhuang et al., 2022). The literature reveals that planting variety and planting structure benefit yield. For example, planting a mixture of rice varieties was effective in boosting yields (Li et al., 2009; Zhu et al., 2000). Consequently, this has been widely promoted in China and increased the yield on average by 0.7 tons/ha, resulting in an income increase of 259 million US$. The amount of rice and corn planted has significantly increased as a result of the minimum purchase price for crops, the cost of temporary storage, and the high demand for livestock products (Carter et al., 2012; Yu and Jensen, 2010). A previous study found that the minimum purchase price is a key factor in the northeast of China, Jiangxi province, Anhui province, and Jiangsu province, which may extend the positive contribution of yields in these regions, and therefore, outweigh other factors (Liu et al., 2020c).

However, yield is not the only factor increasing crop production. Our study also found that an increase in MCI had a positive effect on crop production, but its impact was considerably smaller (Zhuang et al., 2022). Specifically, our findings demonstrate that MCI changes have a direct impact on food production through planting management and land restructuring. For example, the increase in farmers' incomes actively encourages the scientific management of cropland and enhances cropland intensification and crop production (Foley et al., 2011; Huang et al., 2013). As the profitability of staple crops declined from 2004 onwards (NSBC, 2005), crops with higher production and higher MCI (e.g., vegetables) replaced rice crops (Lai et al., 2020; Zhong and Liu, 2007), which resulted in a change of cropping structure (Liu et al., 2016c). However, this is not the case in all regions. Our analysis using county-scale decomposition shows that different degrees of farming intensification have different effects on rising crop production during the first 10 years of the 21st century. Some counties located in the North China Plain had a positive impact of crop production, which was due to the use of agricultural inputs (e.g., fertilizers, pesticides, etc.) as well as improved irrigation methods resulting in an increase of both yield and MCI (Guo et al., 2010; Rodell et al., 2018). The increase in the MCI in Henan province has contributed to the increase in crop production, which can be explained by the expansion of vegetable cultivation (Wang et al., 2018a). Despite the fact that counties located along the southeastern coastal area tend to have a more favorable climate for agriculture and stronger economic development, they are typically characterized by a negative contribution to overall crop production due to intensive urbanization.

Our results also showed that while the growth of NP represents an increase in crop production, the drop in the national MPS had a negative impact on the increase in crop production at a national scale. This is undeniable given that the rapid decrease in MPS and gain in NP are a direct result of increasing cropland fragmentation across China (Fang et al., 2016). Although haphazard and unplanned cultivation partly increased the cropland NP (i.e., recultivation mainly occurred in mountain areas due to conversion of grassland and woodland to cropland) (Gao et al., 2019), it was unable to compensate for the loss in crop production due to the sharp decline in MPS as a result of the cropland area lost within the given period. When we look more closely at the NP and MPS impacts at the county scale, we discover important inter-regional differences. As observed, the shrinkage in cropland size had a harmful effect on food security in the North China Plain and in the northeast of China, where the terrain is flat and mechanized agriculture is widely established. Rapidly expanding urbanization in those areas resulted in a conversion of large-scale cropland to more scattered patches. There are more patches and obviously more plots for agriculture, but the mean patch area per cropland is declining. This means that more agricultural inputs (e.g., fertilizers and pesticides) will be needed to produce equal crop output (Lu et al., 2018; Ren et al., 2019). It has been proven that more efficient planting management (e.g., after joining multiple small cropland patches into larger ones) results in a more rational allocation of agricultural resources (Ju et al., 2016). This may result in higher overall crop production. For example, farmers can lower their costs, and hence maximize their agricultural output, by making more use of scientific insights into soil quality related parameters. Furthermore, Mekki et al. (2018) found that farmland fragmentation significantly affected the decision-making process with regard to crop allocation. This is particularly true for the southern part of China where staple crops (e.g., maize, rice) do not support the income of local farmers and as such have been replaced by crops with a higher economic return (i.e., cash crops) or in extreme cases croplands have been abandoned (Qiu et al., 2020; Yan et al., 2016). The shift to more fragmented croplands in staple crop-producing areas indicates that this factor could increasingly offset gains from improved yield and MCI.

Altogether, the present factor decomposition of crop production facilitates the identification of future constraints and opportunities for the Chinese agricultural sector. Until now, science and technology have had a particular focus on increasing food through intensifying agriculture practices, resulting in yield and MCI increases, in order to avoid an expansion of cropland area. However, this study highlights that besides intensifying agriculture practices, large-scale utilization also has the potential to boost crop production in many regions across China. In a nutshell, a better understanding of the drivers of change in crop production can suggest strategies for policymakers to address the SDGs focused on enhancing future food security.

5. Conclusions

This study shows that yield, MCI, NP, and MPS are key factors affecting crop production changes across China between 2000 and 2010. However, the results highlight that the spatial distributions of the contribution of these factors were remarkably different. By applying a LMDI approach, we found that yield had the most important positive effect on crop production increase with a relative contribution of +77%. In addition, MCI (+27%) and NP (+21%) had a positive effect on crop production changes, whereas MPS had a negative impact. The counties characterized by a positive effect of yield accounted for 62% of the total number of counties, which were mainly situated in the north of Hebei and Shanxi provinces. The counties where MCI had a positive effect on crop production increase accounted for 54% of the total number of counties, which were mainly located in Heilongjiang province. MPS and NP had a positive impact on crop production increase in 52% and 37% of the total number of counties, respectively, which were mainly located in the North China Plain. Despite the overall increasing trend in crop production, some counties were characterized by a decrease and therefore require special attention. When looking into the areas characterized by a decrease in crop production, a decline in MCI and yield had a primary negative effect on crop production, accounting for 33% and 28% of the counties with decreasing crop production, respectively. Furthermore, MPS and NP were the main factors associated with a decrease in crop production in counties scattered across China, representing 24% and 15% of the counties with decreasing crop production, respectively. The negative contributions to cropland production increase were mostly due to a decline in large scale farming. Besides stabilizing yield and maintaining the total NP, land consolidation and financial assistance for land transfer and advanced infrastructure are critical strategies that could help to counter the fragmentation of croplands and MCI, and therefore make an important contribution to the sustainable development of agriculture in China.

6. Supplementary information

All supplementary information mentioned in this chapter is publicly available on the published paper's webpage at:
https: //www.mdpi.com/article/10.3390/rs14246399/s1

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Chapter 3

Cropland Dynamics across the Yangtze River Basin, China

This chapter is based on:

Long, Y., Sun, J., Wellens, J., Colinet, G., Wu, W & Meersmans, J. (2024). Mapping the spatiotemporal dynamics of cropland abandonment and recultivation across the Yangtze River Basin. Remote Sensing. 2024, 16(6), 1052

Abstract

Whether China can achieve the United Nations' Sustainable Development Goals (SDGs) largely depends on the ability of main food-producing areas to cope with multiple land use change challenges. Despite the fact that the Yangtze River basin is one of the key regions for China's food security, the spatiotemporal dynamics of cropland abandonment and recultivation remain largely unexplored in this region. The present study assesses the evolution of the agricultural system within the Yangtze River basin between 2000 and 2020 by mapping cropland abandonment and recultivation using MODIS time series and multiple land cover products. The results highlight a widespread cropland abandonment process (i.e., 10.5% of the total study area between 2000 and 2020), predominantly in Western Sichuan, Eastern Yunnan, and Central Jiangxi. Although 70% of abandoned cropland is situated in areas with slopes less than 5°, the highest rates of abandon-ment are in mountainous regions. However, by 2020, 74% of this abandoned cropland had been recultivated at least once, whereas half of the abandoned croplands got recultivated within three years of their initial abandonment. Hence, as this is one of the first studies that unravels the com-plex interaction between cropland abandonment and recultivation in a spatiotemporal explicit context, it offers (i) scientists a novel methodological framework to assess agricultural land use is-sues across large geographical entities, and (ii) policy-makers new insights to support the sustain-able transition of the agricultural sector.

1. Introduction

Scientific interest in cropland abandonment and recultivation has increased due to concerns about food, feed, fiber, biofuel security, and environmental sustainability (Foley et al., 2011; Lambin and Meyfroidt, 2011). Since the 1950s, a substantial expanse, encompassing hundreds of millions of hectares worldwide, has undergone this transition. For example, satellite imagery revealed that approximately 78.5 ± 16.4 million hectares (Mha) of cropland was abandoned between 2003 and 2019, either permanently or temporarily (of which 18.5 ± 3.9 Mha, or 24%, is now forested) (Chazdon et al., 2020; Potapov et al., 2022; Ramankutty et al., 2018; Winkler et al., 2021). This trend is particularly pronounced in regions such as Europe, North America, East Asia, and Latin America (Díaz et al., 2011; Estel et al., 2015; Yoon and Kim, 2020; Yu and Lu, 2017; Zhu et al., 2021), and can be linked to drivers like urbanization and environmental degradation (Gellrich et al., 2007; Næss et al., 2021; Prishchepov et al., 2021b; Rey Benayas et al., 2007). Furthermore, local and distant socio–economic factors (e.g., migration and rural labor dynamics) are important drivers of land abandonment, even in areas with sustainable agriculture (Mottet et al., 2006).

Cropland abandonment impacts both the environment and society, notably by affecting the delivery of multiple ecosystem services, including biodiversity, climate regulation, and food security (Feng et al., 2005; Fischer et al., 2012; Kuemmerle et al., 2011; Raj Khanal and Watanabe, 2006). Despite it posing challenges for food security, it also offers an opportunity to restore natural ecosystems (Chazdon et al., 2020; Xie et al., 2019). However, the benefits, particularly carbon sequestration, depend on the abandonment duration, with long-term duration offering greater climate regulation potential (Wertebach et al., 2017). It has been recently reported that abandonment can be ephemeral (Zheng et al., 2023), particularly in cropland-scarce regions. Hence, obtaining an improved understanding of the dynamics of cropland abandonment and recultivation is crucial in order to assess its impact on the delivery of multiple ecosystem services and support policy-makers in developing sustainable solutions for the future (Du et al., 2021; Kolecka, 2018).

The definition of cropland abandonment is broad, not only considering the temporal aspect of it, but also from a of land use type/intensity point of view. Generally, cropland abandonment can be defined as the cessation of the use of existing cropland by farmers on their own initiative. However, there is no consensus as regards the duration (Bell et al., 2023). For example, the Food and Agriculture Organization (FAO) considers a duration of two to five years, whereas, in some studies conducted in China, cropland abandonment could be defined as “cropland left idle for a year or even a season” (Li et al., 2022). In recent years, geographers have developed a new definition of cropland abandonment from the perspective of land use type/intensity of use, focusing on the ecological evolution of abandonment. They analyzed the dynamics of cropland in Europe and pointed out that cropland abandonment is “the replacement of anthropogenic farmland by early successional natural vegetation” (Alix-Garcia et al., 2012; Prishchepov et al., 2021a). As such, complex land use activities and long-term monitoring methods are needed to identify cropland abandonment over time at the regional scale.

Spatial data covering vast geographical entities are essential for in-depth analyses of the spatial and temporal dynamics of pattern as well as for assessing the associated interaction between cropland abandonment and recultivation. The latter will facilitate the identification of driving forces and environmental impacts of agricultural land dynamics. Although this research is of great societal importance, collecting accurate spatiotemporal explicit data remains one of the main challenges. Statistical data from traditional land use surveys, such as from the China Household Finance Survey (CHFS) from the Southwestern University of Finance and Economics (Xu et al., 2019a), do not provide us with the required quality due to the lack of spatial detail (typically providing average values at regional, provincial, or municipal level), hindering the detection of the rather complex spatiotemporal trends determining the interplay between cropland abandonment and recultivation.

Over the last two decades, important advances have been made in the context of cropland abandonment monitoring by using a variety of new satellite-derived data (Estacio et al., 2023; Goga et al., 2019; Oliphant et al., 2019). For instance, the fusion of Sentinel-1 (synthetic aperture radar sensors) and Sentinel-2 (optical sensors) imagery helped in cropland abandonment monitoring in tropical areas (Huang et al., 2019). However, due to the first launch of the Sentinel satellite being in 2014, it is impossible to achieve long time series monitoring. As such, Landsat is considered to be an important data source for long-term cropland abandonment detection (Prishchepov et al., 2012b; Yin et al., 2020). For example, Xiao et al. (2019) monitored cropland abandonment between 1990 and 2017 in counties of the Shandong Province using Landsat and HJ1A imagery. However, obtaining accurate data over brief intervals using Landsat poses challenges, mainly due to cloud interference (Alcantara et al., 2012). As such, previous efforts to map cropland abandonment indicated the complexity of Landsat-based analyses due to difficulty in extracting reliable and sufficient data when considering relatively short periods of time across large areas (Cao et al., 2020b). Moreover, the varying definitions of "abandonment" hinder its identification and mapping. Cropland abandonment is commonly defined as agricultural land that remains unused for at least two to five years (FAO, 2016; Pointereau et al., 2008). However, the prevalence of short cultivation periods introduces challenges in differentiating abandoned cropland from fallow cropland (Yin et al., 2020). In contrast to other land use/land cover classifications, considering crop rotation cycles and/or farming practices is crucial to distinguish cropland abandonment from fallow cropland (Alcantara et al., 2012). Given that cropland abandonment entails a longer cessation period than when land is lying fallow, ascertaining whether the land use transition duration exceeds a crop rotation cycle is essential. Consequently, intervals between temporal snapshots exceeding a typical crop rotation cycle may lead to the misidentification of many fallow areas as abandoned croplands. Therefore, assessing multiple consecutive years is critical to accurately determine whether a field has indeed been abandoned (Estel et al., 2015; Löw et al., 2015; Löw et al., 2018). Using regular, consecutive time series data, like those provided by The Moderate Resolution Imaging Spectroradiometer (MODIS), will be key to minimizing the risk of misclassification of temporarily fallow land within a crop rotation as being abandoned cropland.

MODIS offers comprehensive observations for assessing regional cropland change as it effectively minimizes the impacts of viewing geometry, cloud cover, and aerosol loading while maintaining a suitable temporal resolution for consistent large-scale abandoned cropland monitoring (Fensholt et al., 2015). A study utilized MODIS normalized difference vegetation index (NDVI) products to map abandoned agricultural land across Eastern Europe, achieving an overall classification accuracy of 65% (Alcantara et al., 2012). A similar study identified active and fallow land in Europe using MODIS-NDVI time series to subsequently map the extent of abandoned croplands (Estel et al., 2015). A recent study in China combined MODIS data with phenological metrics to map land use change dynamics between 2001 and 2015, which enabled the identification of a remarkable cropland abandonment process across the mountainous region of Southwest China (Han and Song, 2019). The results of the study highlighted that the mapping accuracy of abandoned cropland is significantly influenced by the quality of the data retrieved from the selected samples. The current methods of sample collection may not keep pace with the rapidly evolving requirements of monitoring, and this especially becomes an issue when considering large areas (Luo and Moiwo, 2022). This challenge underscores the need for more diversified and rapid sample collection strategies to enhance monitoring efficiency and accuracy.

Indeed, collecting reliable sample points, especially across vast regions, is labor intensive (Fritz et al., 2012). Although the quality of spectral reflectance data obtained from the remote sensing imagery is vital to set-up a thorough land use classification, this reflectance, and its relation to various land uses, may change yearly depending on, for example, inter-annual variation in meteorological conditions. This is particularly true for cropland dominated areas. As such, annual training, linking spectral information to a set of given land use classes, is essential. Furthermore, automating reference data generation, accounting for spatial and field attributes, is a key methodological procedure (Tong et al., 2020). A pragmatic solution combines established land use classification products, such as MCD12Q1 and GlobeLand30. This approach allows for the extraction of pixels from identical positions across two or more products that have been classified under the same land cover categories, thereby enabling the accumulation of sufficient samples. Using this methodological approach for annual land cover mapping based on Landsat has proven to be effective (Li et al., 2021a), suggesting its potential efficacy for annual cropland mapping. The latter highlights the importance of setting up a robust land use classification approach using a variety of reliable public datasets in order to facilitate an efficient sample collection procedure and obtain reliable cropland abandonment maps covering vast geographical entities.

The Yangtze River basin is important in global food production, and food production is highly sensitive to changes in cropland area. However, since 2000, the region has seen dramatic changes in cropland area and a significant decline in cropping intensity (Yan et al., 2019). The Yangtze River basin in China is a focal point for the nation's strategic development, as was highlighted in the "Guiding Opinions on Promoting the Development of the Yangtze River Economic Belt Relying on the Golden Waterway" released by the China State Council in 2014 (http://www.gov.cn/, accessed 1 December 2022). Since 2003, the basin has experienced increasing migrant wages and rural outmigration, resulting in a widespread agricultural abandonment (Zhang et al., 2019). The "Yangtze River Economic Belt Development Plan" (https://cjjjd.ndrc.gov.cn/, accessed 1 December 2022) predicts increased urbanization in the next two decades, possibly exacerbating cropland abandonment (Chen et al., 2020; Li et al., 2016a). As this cropland abandonment process poses threats to food security, recent studies and land management projects in China have underlined the potential for recultivating abandoned croplands to support food production in dominant crop production regions such as the Yangtze River plain (Chen et al., 2023; Liang et al., 2022; Schulte et al., 2021). The region's total nature-based carbon sequestration potential is 15 million tons, and, therefore, may make a significant contribution to climate mitigation efforts at the national scale (Gu et al., 2021; Quan et al., 2023). Quantifying cropland abandonment impacts on climate mitigation and food security is important to assess the trade-off between these two vital ecosystem services. As such, accurate data on abandonment and recultivation patterns are crucial to conduct this research. Currently, the remote sensing based studies for monitoring of cropland in the Yangtze River basin are diverse and cover various aspects of land use and environmental monitoring, including urbanization (Liu et al., 2020a), water and soil monitoring (Li et al., 2020), and crop patterns (Jiang et al., 2022). However, studies focusing on the spatiotemporal dynamics of the interaction between cropland abandonment and recultivation in this region are lacking.

In this study, we define "cropland abandonment" as the conversion of agricultural land from cropland to natural vegetation after two consecutive years of non-cultivation. This definition facilitates the distinction between short-term fallowing and long-term abandonment, which is crucial when examining crop rotation cycles and/or farming practices. This definition is in line with previous studies of cropland abandonment monitoring carried out across the Yangtze River basin (Dong et al., 2023; Han and Song, 2019; Hou et al., 2021). Our aim is to map the extent and timing of abandoned and recultivated cropland at the watershed scale using MODIS time series data, and to reveal the spatial and temporal interactions between these processes in order to obtain a more comprehensive understanding of the complex land use dynamics across this study area. To do so, we proceeded as follows:

(1) We used a strategy to quickly generate classifier sample data based on existing land use products, and created annual land cover maps suitable for a large scale area.
(2) We mapped the extent and timing of cropland abandonment and recultivation based on continuous time series land cover data.
(3) We analyzed the cropland abandonment intensity (i.e., frequency and duration) and the spatial and temporal interaction with recultivation.

2. Materials and methods

2.1. Study areas

The Yangtze River basin is located in Southern China, and includes nine provinces and two municipalities (Figure 3-1). Covering 21.3% of China's territory, it houses 599 million people. The basin is a major grain producer, accounting for 36.2% of China's grain output in 2019 (China statistical yearbook, 2019, http://www.stats.gov.cn/sj/ndsj/2019, accessed 1 November 2022). Economic activities within the basin have shown remarkable growth, contributing 46.3% to China's GDP in 2018 (China statistical yearbook, 2019). However, this growth has long-term negative environmental consequences, as the region faces habitat loss, biodiversity decline, pollution, and severe soil erosion issues. Consequently, notable reductions in cropland area have been observed in some parts of the region (Zhou et al., 2020), threatening food security at the national level.

Given the extended growing seasons resulting from the warm and wet climate in the study region, crop rotation and continuous monocropping emerge as the two predominant cropping systems. Dryland crops such as wheat, oilseed rape, and maize often yield two harvests per year, illustrated by common rotations like "fallow–wheat–wheat", "rice–rice", "cole–corn", "wheat–corn", "wheat–corn–sweet potato", and "rice–winter crop". These crop rotation schemes are frequently modified to improve the sustainability of agricultural systems; as such a fallow period of one to two years is common.

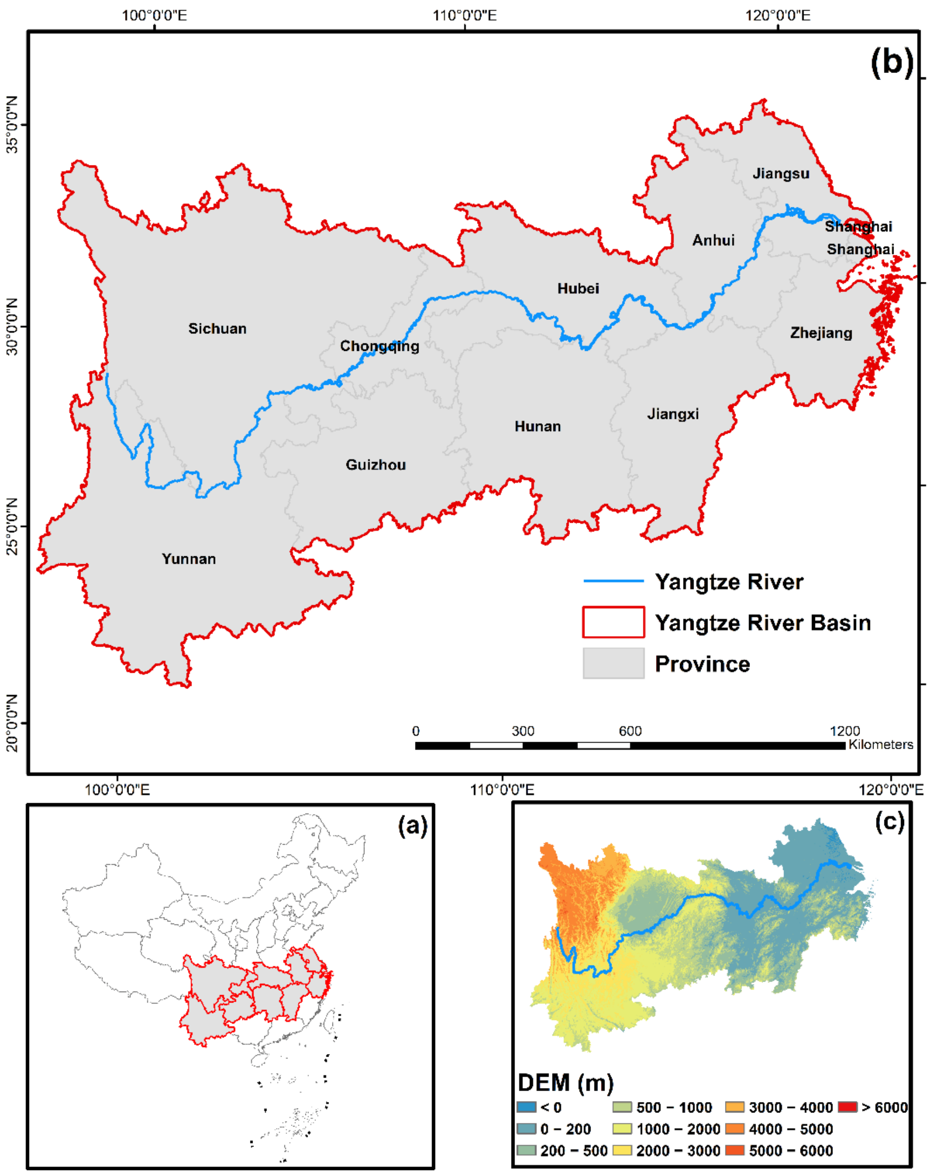

Figure 3-1. Study region. (a) The location of the Yangtze River Basin in China. (b) The nine provinces and two municipali-ties included across the Yangtze River basin. (c) DEM distribution across the Yangtze River Basin.

2.2. Definition cropland abandonment and recultivation

Taking into account the FAO definition, cropland abandonment is a result of a lack of management for at least two to five years (FAO, 2016; GrĂDinaru et al., 2020). We characterized cropland as being abandoned if it had not been cultivated for at least two consecutive years. However, when these abandoned croplands were converted back into cropland, we identify this process as 'recultivation' (Figure 3-2).

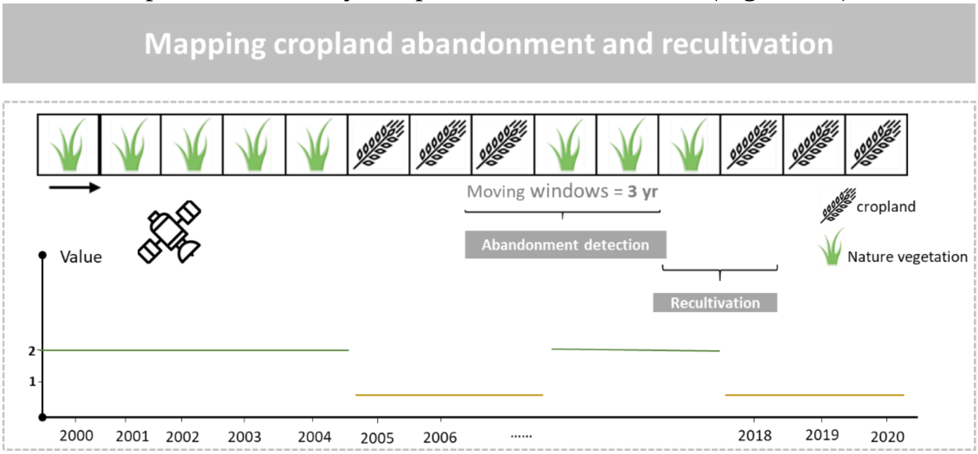

Figure 3-2. Detection of cropland abandonment and recultivation

2.3. Data preprocessing for classification

Figure 3-3 outlines our five-step methodological framework. Step A, NDVI (Normalized Difference Vegetation Index) maps were produced from MODIS imagery. NDVI, calculated as (NIR − Red)/(NIR + Red), where NIR is near-infrared band reflectance and Red is red band reflectance, serves as a crucial tool for differentiating land covers and assessing cropland productivity. Step B, sample data were collected from locations consistently classified across multiple products. To ensure accuracy, at least 10% of these samples were manually verified using high-resolution images. These samples were then divided into training datasets and datasets for accuracy qualification. Employing the Random Forest algorithm (RF) with annual training data, we produced annual land cover maps, whose accuracy was evaluated using overall accuracy, kappa, and F1 metrics (He and Ma, 2013; Powers, 2011). Steps C and D, spatiotemporal patterns of cropland abandonment and its intensity (i.e., frequency and duration) were mapped by considering the trajectory of change in this land cover class. Step E, annual recultivation maps were produced based on abandoned cropland and annual land use data. All data analyses were conducted by using Google Earth Engine (GEE) cloud computing platforms and ArcGIS 10.2 ESRI (Environmental Systems Research Institute, 2013).

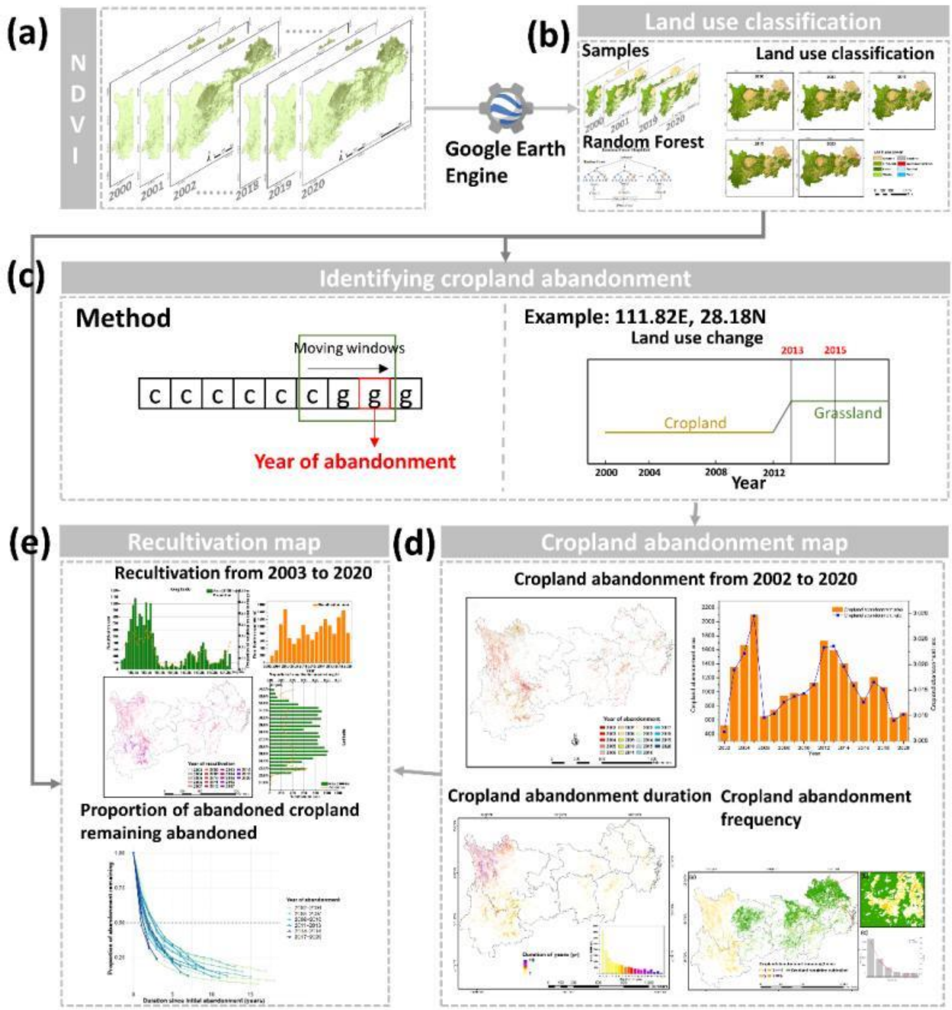

Figure 3-3. Flowchart of the study. (a) Acquisition and reconstruction of MODIS-NDVI from 2000 to 2020. (b) Collection and Utilization of Sample Points for Annual Land Use Classification Using Random Forest Algorithm. (c) Mapping cropland abandonment and recultivation. (d) Spatiotemporal dynamics of cropland abandonment and its intensity. (e) Spatiotemporal dynamics of recultivation.

In this study, a smoothing function was applied to the NDVI time series to counteract noise from clouds, soil, and snow in order to better characterize the growth curve. Initially, pixels labeled as poor quality, snow/ice, or cloud in the QA layer were filtered out from the original NDVI time series. Subsequently, the NDVI profiles were reconstructed for each year of the time series using a weighted Whittaker smoothing algorithm (Atzberger and Eilers, 2011b; Kong et al., 2019).

2.4. *Annual land cover mapping and accuracy assessment*

We obtained an extensive dataset covering our entire study area to collect classification samples. Our sample data were produced based on two data sources: (1) Dense time series land cover products for sample collection, including GlobeLand30 (http://www.globallandcover.com, accessed 1 November 2022), China's National Land Use and Cover Change (CNLUCC) dataset (http://www.resdc.cn, accessed 1 November 2022), MCD12Q1 global land cover maps (https://lpdaac.usgs.gov/products/mcd12q1v006/, accessed 1 November 2022), ESA-CCI (https://www.esa-landcover-cci.org/, accessed 1 November 2022), and Glob-Cover maps (http://due.esrin.esa.int/page_globcover.php, accessed 1 November 2022) (Table 3-1). (2) Dense time series of high-resolution images, like Google Earth Pro© and CLCD for sample correction (Supplementary information S1.2). Initially, a nearest neighbor resampling technique was applied to MCD12Q1, GlobCover, CNLUCC, and ESA-CCI, and a majority filtering technique was applied to GlobeLand30 so that the resolution of all datasets was consistent with the 250 m resolution of the MODIS-NDVI dataset. We generated random points to obtain land cover from at least 3 out of 5 of these land cover products each year (the distance between all random points generated was set to 500 m to avoid saturation sampling). Random points with high feature consistency are considered to be consensus samples. As a minimum threshold, there should have been an agreement on at least two-thirds of the land cover products each year. These consensus samples, exceeding 10,000 in number, demonstrated stable land cover types and high consistency across various maps, especially in mountainous regions (Table S2 and S3).

Subsequently, we selected random points with high feature consistency and manually corrected a 10% random sample for each land cover class. For less represented classes like shrubs and wetlands, we increased the random sampling to 15%. Sampling ratios were based on established methodologies (Zhu et al., 2021), with random screening conducted through ArcGIS 10.2. The correction consisted of two methods using Google Earth and CLCD. (1) Visual interpretation using historical Google Earth imagery was performed as a minimum if the corresponding data existed. If these data were not available, (2) the correction was based on the CLCD land cover product. First, the relative surface cover of each land cover class was calculated within a 250 m resolution grid consistent with our MODIS-NDVI pixel, and classes with more than 50% cover within the grid cell were designated as correction land cover (Figure S1). However, if no land cover category had 50% coverage, the point was discarded from the analysis.

Finally, approximately 70% of the total consensus sample points were allocated to the Random Forest classifier for training, and the remaining 30% were used for quantifying the accuracies. This allocation ratio has been demonstrated to enhance classification robustness (He et al., 2022; Mao et al., 2020; Zhao et al., 2022).

Table 3-1. Auxiliary dataset used for collecting annual samples. Our selected datasets have been shown to have high accuracy of land cover classification across the China (Yang et al., 2017).

Year	GlobeLand30	CNLUCC	MCD12Q1	ESA-CCI	GlobCover
2000	2000	2000	2001	2000	
2001	2000	2000	2001	2001	
2002	2000	2000	2002	2002	
2003		2005	2003	2003	2005
2004		2005	2004	2004	2005
2005		2005	2005	2005	2005
2006		2005	2006	2006	2005
2007		2005	2007	2007	2005
2008	2010	2010	2008	2008	2009
2009	2010	2010	2009	2009	2009
2010	2010	2010	2010	2010	
2011	2010	2010	2011	2011	
2012	2010	2010	2012	2012	
2013		2015	2013	2013	
2014		2015	2014	2014	
2015		2015	2015	2015	
2016		2015	2016	2015	
2017		2018	2017	2015	
2018	2020	2018	2018		
2019	2020	2018	2019		
2020	2020	2020	2019		

We used the RF in GEE for annual land cover classification. RF implementation in GEE enables large-scale classification at the pixel level. Similar to many other models, RF's effectiveness is sensitive to the selection of hyperparameters and the training data employed (Jin et al., 2019). To date, RF is considered to be the most widely used algorithm for land cover classification using remotely sensed data (Tamiminia et al., 2020), due to the fact that only two parameters (number of trees: ntree and maximum number of features to try: mtry) need to be optimized. In GEE, mature RF algorithms have been included for direct use.

We included three key parameters in our random forest model: the smoothed MODIS-NDVI dataset (46 images per year), the number of filtered sample points, and the random forest parameters (ntree and mtry). Based on the recommendations of previous studies (Ghimire et al., 2012) and our large sample data, we first select 120 trees (ntree = 120) while setting mtry as the default value. We will adjust the number of trees several times according to the classification results in order to achieve the best classification results.

For classification accuracy qualification, we generated annual confusion matrices, calculating overall accuracy (OA), producer's accuracy (PA), user's accuracy (UA), and the kappa index. We also used the $F1$ score for each class accuracy assessment.

$$OA = \frac{Number\ of\ correctly\ classified\ samples}{Total\ number\ of\ samples} \tag{1}$$

$$PA = \frac{Number\ of\ correctly\ classified\ samples\ of\ the\ category}{Total\ actual\ samples\ of\ the\ category} \tag{2}$$

$$UA = \frac{Number\ of\ correctly\ classified\ samples\ of\ category}{Total\ samples\ classified\ into\ the\ category} \tag{3}$$

$$F1 = 2 \times UA \times PA\,/\,(UA + PA) \tag{4}$$

Where $F1$ score, a harmonic mean of user's and producer's accuracy, is advantageous when learning from imbalanced data. $F1$ score ranges from 0 to 1 with higher score indicating better classification performance.

2.5. Annual Cropland Abandonment and Recultivation Mapping

We conservatively classified a cropland pixel as abandoned only if it changed into natural cover (Figure 3-3). We excluded lands converted into wetlands, impervious surfaces, or water bodies. Additionally, forested areas were omitted from our analysis, as two years is insufficient for abandoned cropland to change into mature forest ecosystems.

There have been concerns about the overestimation of abandoned croplands in some parts of the world, e.g., due to the large-scale intentional afforestation, such as "Grain for Green" program in China (known as "GGP", which converted croplands located on slopes of more than 25° into grassland/forest (Long et al., 2006)). Such overestimation may result in wrong projections of the amount of land available for carbon sequestration, nature restoration, or afforestation projects through cropland abandonment, as intentional afforestation already represents the shift in land use (Hong et al., 2024; Næss et al., 2021). To distinguish our cropland abandonment from GGP, we used a Digital Elevation Model (DEM, 250 m resolution based on SRTM 90 m, https://www.resdc.cn, accessed 1 November 2022) to restrict our study area to slopes under 25°.

Upon detecting cropland abandonment, we created annual maps covering the period from 2002 to 2020. This enabled the computation of annual relative cropland abandonment area proportion to cropland area ($RCAP$), frequency, and duration. Frequency indicates how often a specific area was identified as abandoned from 2002 to 2020, while duration measures the time span from a site's initial abandonment identification to either recultivation or 2020.

$$RCAP^{T+2} = Area_{CA}^{T+2} / Area_{C}^{T} \tag{4}$$

where $RCAP^{T+2}$ denotes relative cropland abandonment area proportion in the given region, $Area_{CA}^{T+2}$ (10^3 ha) is the cropland abandonment area which included cropland identified in year (T) that is considered abandoned after two years ($T+2$)

in the given region, and $Area_C^T$ (10^3 ha) represents the total cropland area in the given region in year (T). In this study, T ranges between 2000 and 2018 when considering cropland.

A pixel reverted from abandoned to cropland was classified as recultivated. This method helped track the change in the proportion of abandoned land over time, offering more precise insights than average abandonment duration.

3. Results

3.1. Land cover maps and accuracy

Throughout all our land-cover maps of the Yangtze River Basin (from 2000 up to 2020), cropland, forest, and grassland are covering c. 35%, c. 40%, and c. 20% of the total area, respectively (Figure 3-4). More precisely, cropland is mainly found in the agriculturally favorable flat terrains of Eastern Sichuan, Anhui, and Jiangsu. Forests, on the other hand, are mainly found in the western areas, especially in Yunnan and Guizhou. Meanwhile, grasslands are chiefly located in the northwestern part of Sichuan and Yunnan.

The sequence of land use change maps from 2000 to 2020 revealed a significant decrease in cropland. For instance, certain regions of Yunnan changed from cropland to grassland over these two decades (Figure 3-5), in addition to the encroachment of cropland by the development of the Yangtze River urban agglomeration.

Our validation of the 2000-2020 classifications (Figure 3-6 and 3-7) revealed an OA ranging between 0.82 and 0.85. The years 2018-2020 had the lowest average OA at 0.82±0.02 (95% confidence interval), while 2009-2011 had the highest OA at 0.85±0.002. The Kappa index follows this trend in accuracy. Land cover specific F1 scores was highest for forest (0.90±0.01), followed by water (0.89±0.02), cropland (0.84±0.01), grassland (0.84±0.01), and impervious surface (0.83±0.03). Significantly lower F1-scores were observed for wetland (0.41±0.1) and shrubs (0.47±0.03).

We compared our cropland classification results with the CLCD (Yang and Huang, 2021) classification for each individual province. Although this has been done annually, in Figure 3-8, we presented the results for the years 2000, 2005, 2010, 2015, and 2020 as examples. Our analysis revealed a strong correlation between our maps and the CLCD-30m cropland layer for the majority of provinces.

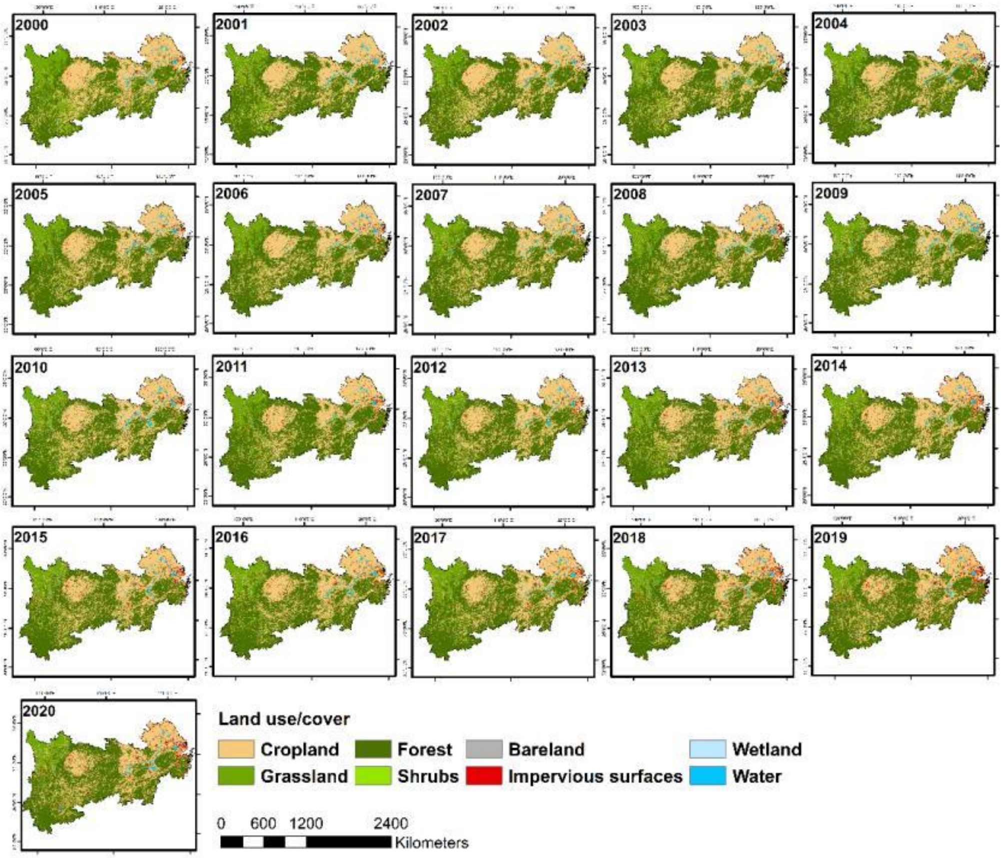

Figure 3-4. Annual land use classification across the Yangtze River Basin. Eight types of land use cover were considered, i.e. cropland, grassland, forest, shrubs, impervious surface, wetland, and water.

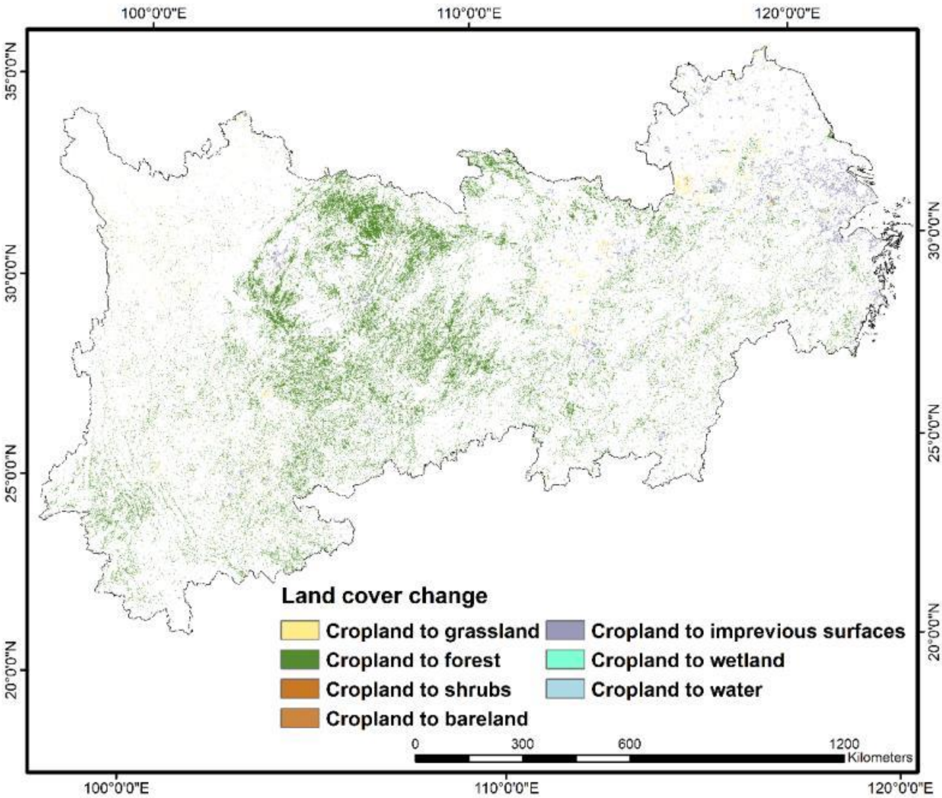

Figure 3-5. The spatial pattern of cropland changes from 2000 to 2020 across the Yangtze River Basin.

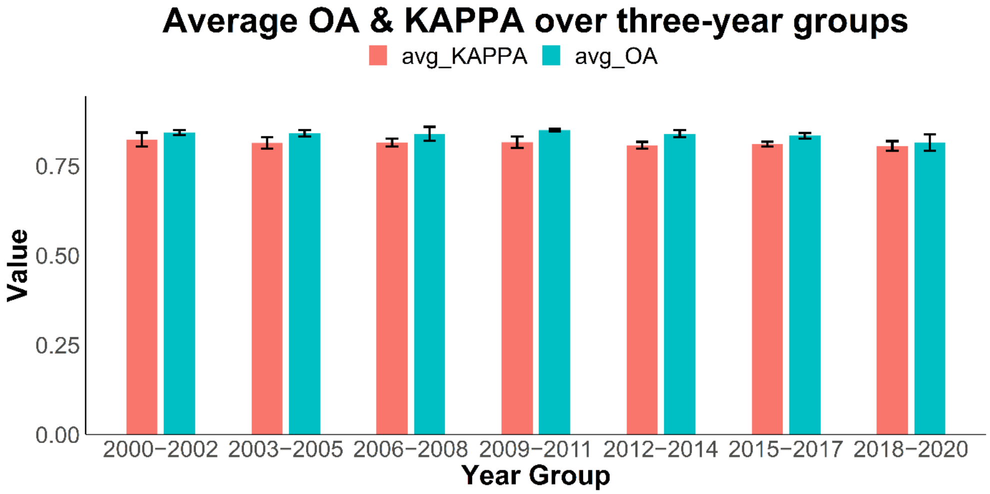

Figure 3-6. Accuracy estimation of LCLU. Overall accuracy (OA) and kappa index reflecting the overall land cover classification accuracy. Bar charts correspond to 3-year group. Error bars indicate 95% confidence intervals.

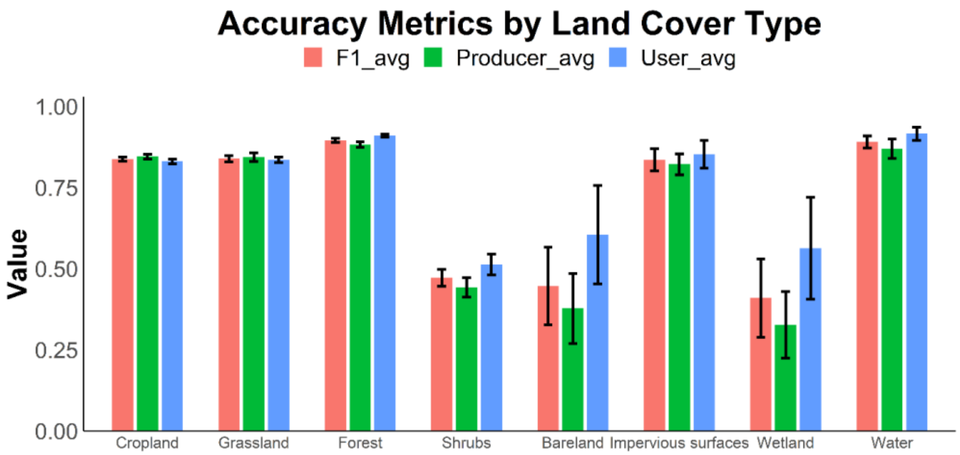

Figure 3-7. Accuracy estimation of classes (i.e. user's accuracy, producer's accuracy and F1). F1 highlights the classification accuracy of each class. The bar charts correspond to the average value between 2000 and 2020, whereas the error bars indicate 95% confidence intervals.

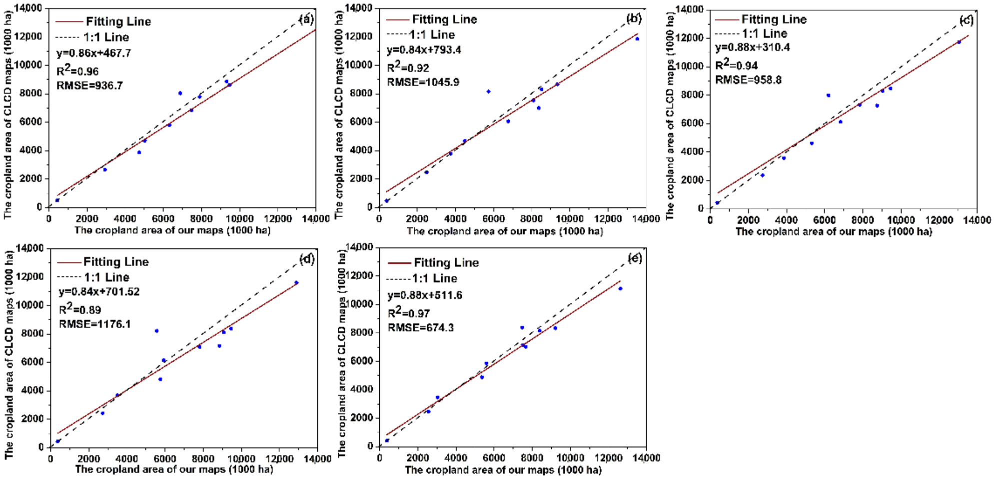

Figure 3-8. Province wise cropland area comparisons between the present study and CLCD-30m cropland layer considering five points in time (a) 2000, (b) 2005, (c) 2010, (c) 2015, (e) 2020.

3.2. Spatiotemporal analysis of cropland abandonment

The annual cropland abandonment map illustrates widespread abandonment throughout the entire study region (Figure 3-9). However, the high-altitude agricultural zones in Sichuan and Yunnan as well as some distinct areas Jiangxi and Zhejiang experienced the highest rate of abandonment. About 60% of these abandonments lie between longitudes 99° and 104°E, and another 25% between 113° and 117°E (Figure 3-9(b)). When considering latitudinal spread, 88% of abandoned croplands are positioned between latitudes 25° and 33°N as depicted in Figure 3-9(d).

Analyzing the annual rate and magnitude of abandonment reveals a fluctuating trend from 2002 to 2020 (Figure 3-9(c)). An increasing trend was observed from 2002 to 2005, followed by a sharp decrease in 2006. Then, a gradual rise from 2006 to 2012 was seen, ending with a remarkable decline post-2012. Throughout this period, an estimated 21490×10^3 ha of cropland were abandoned. The annual figure varied between 526×10^3 ha to 2104×10^3 ha, with relative cropland abandonment area proportion (RCAP) fluctuating between 0.68% and 3%. Notably, 2005 has been characterized by the highest abandonment rate, while 2002 with the lowest.

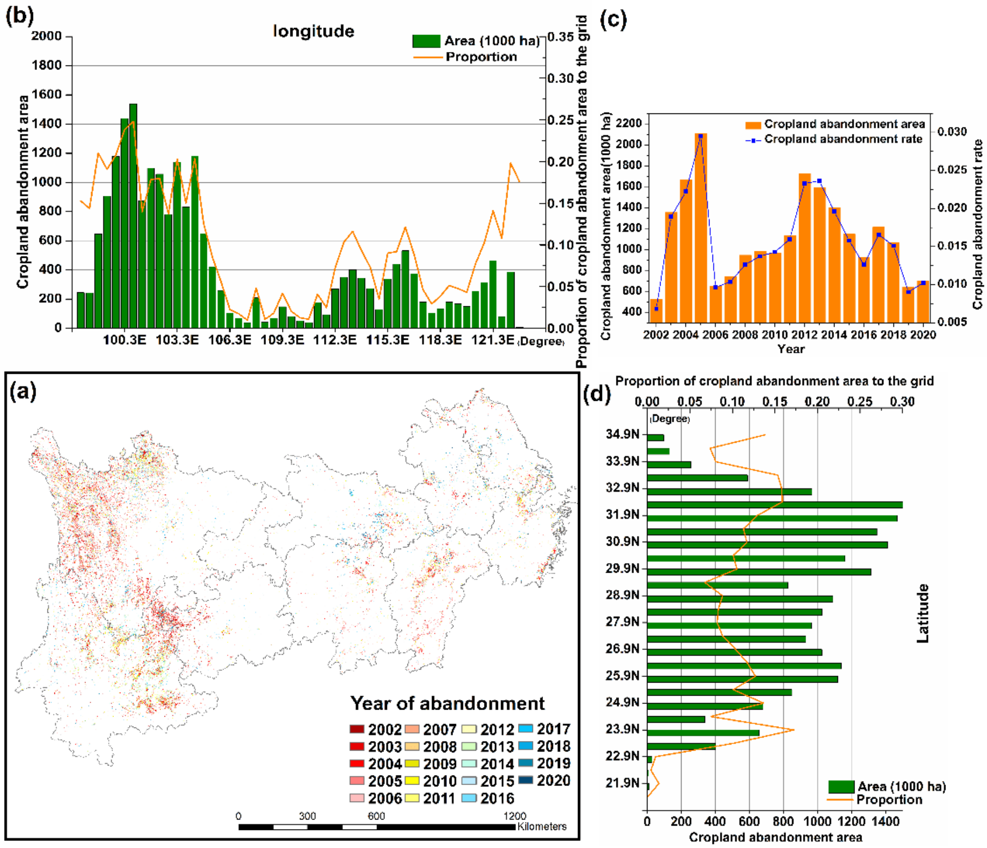

Figure 3-9. The spatial pattern of cropland abandonment and distribution across the Yangtze River basin. (a) The spatiotemporal pattern of cropland abandonment from 2002 to 2020. The red colors represent pixels that were abandoned earlier, while the blue colors are pixels that have been abandoned more recently. (b,d) Accumulated abandoned area (green bar) along longitudinal and latitudinal gradients (0.5°). The orange line represents the proportion of cropland abandonment area as compared to the total land area at the corresponding latitude/longitude. (c) Annual cropland abandonment area and RCAP in the period 2002–2020.

The abandonment frequency map in Figure 3-10 shows varied patterns of abandonment across the region. The abandonment was categorized into three frequency types: low (1–2 times), moderate (3–4 times), and high (5–6 times). The low-frequency abandonment is widespread, especially in Western Sichuan and Yunnan as well as Eastern Jiangxi and Zhejiang. Conversely, the moderate frequency follows a similar distribution, albeit less pronounced in areas such as Sichuan and Eastern Yunnan. High-frequency abandonment is chiefly found in the mountainous regions of Sichuan and Yunnan, accounting for a mere 0.4% (or 82 × 10^3 ha) of the total abandonment over the study period. A remarkable 76% (or 16,310 × 10^3 ha) of the total area experienced low-frequency abandonment, as highlighted in Figure 3-10(c).

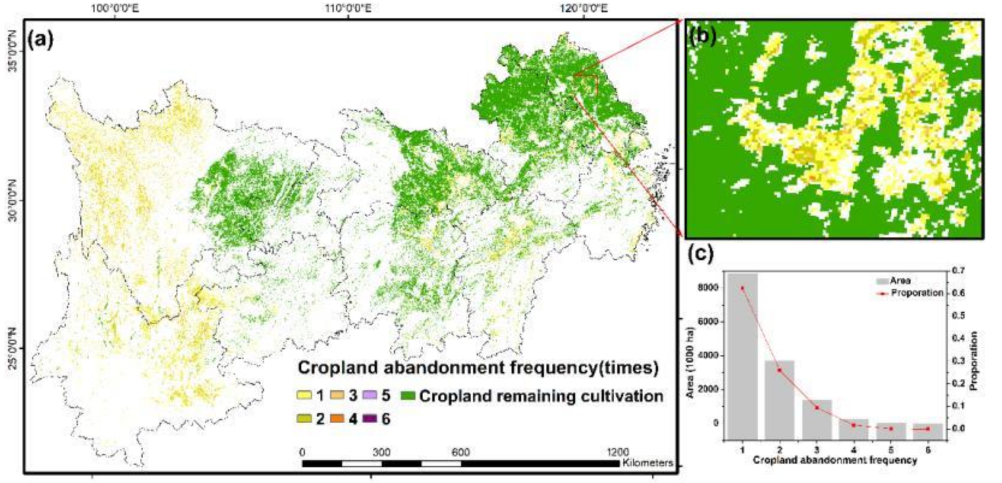

Figure 3-10. The spatial pattern of frequency of cropland abandonment and distribution from 2002-2020 across the Yangtze River Basin. (a) The spatial pattern of cropland abandonment frequency. Cropland remaining cropland (green) represents pixels that remain cropland continuously until 2020. The color-coded frequency scale represents low frequency in shades of yellow (1 - light yellow, 2 - dark yellow), medium frequency in shades of orange (3 - light orange, 4 - dark orange), and high frequency in shades of purple (5 - light purple, 6 - dark purple); (b) Partially enlarged view, legend as in (a); (c) Histogram of abandonment frequency.

Our analysis determined how long a specific pixel of abandoned cropland re-mained abandoned before being changed into another form of land cover (Figure 3-11). The abandonment durations ranged from 1 to 19 years. Although the region's average abandonment duration is relatively short, i.e., averaging around 5.5 years, in regions like Sichuan and Yunnan, the abandonment often surpassed 15 years. The central provinces like Hubei and Hunan typically saw abandonment durations between 5 and 13 years. In terms of the overall landscape, about 25% of the abandoned land reverted after a year, and only 1% remained abandoned for 19 years. Furthermore, there was a 61% probability of the cessation of cropland abandonment if it lasted for five years. Conversely, areas abandoned for over 13 years saw a sharp decline in recultivation likelihood, with only 10% undergoing this process.

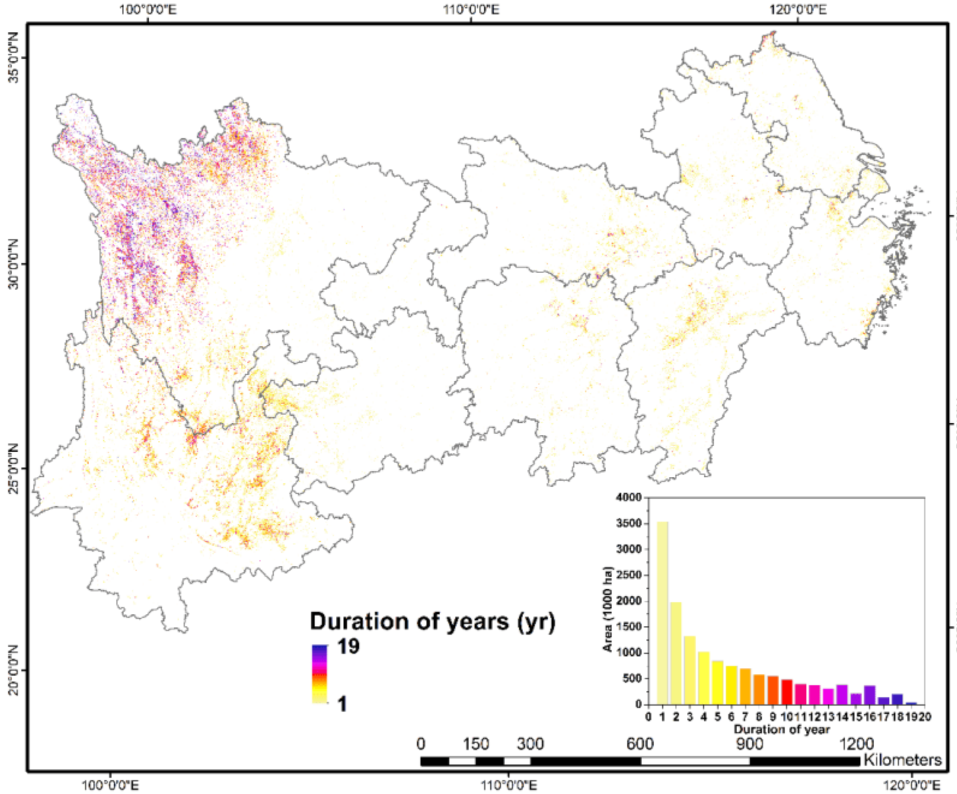

Figure 3-11. The spatial pattern of cropland abandonment duration (in years) across the Yangtze River Basin. The grey bar graph in the lower right corner represents the area of cropland abandonment with different abandonment durations.

Figure 3-12 shows the proportion of abandoned cropland remaining abandoned depending on the initial abandonment date (i.e., considering periods of three years). This figure illustrates a general trend of fairly rapid recultivation of abandoned cropland. More precisely, over half of the abandoned croplands got recultivated within just three years. This curve indicates that the loss pace tends to slow down as the abandonment duration extends. Yet, a more detailed look highlights an increasing trend in recultivation rates, with the most recently abandoned croplands (e.g., initial abandonment period 2017–2019) being recultivated faster compared to croplands that was abandoned in the early 2000s.

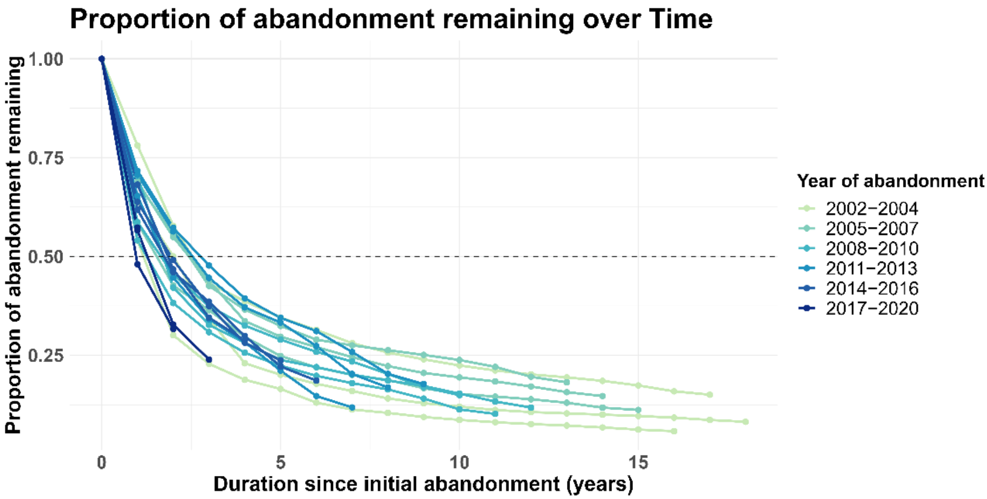

Figure 3-12. The proportion of abandoned cropland remaining abandoned. The temporal trend showing the proportion of abandoned cropland remaining abandoned over time. The horizontal dashed black line shows a proportion of 0.5, indicating the point where half of abandoned croplands have been recultivated.

3.3. Spatio-temporal analysis of recultivation

Our study indicates that the spatial patterns of cropland recultivation mirror those of cropland abandonment, with both being predominantly concentrated in the western part of the study area (Figure 3-13). The process of recultivation predominantly occurred between the longitudes of 99°E to 105°E and the latitudes of 25°N to 33°N (Figure 3-13(b,d)). By 2020's end, 15,857 × 10^3 ha of abandoned cropland had been recultivated, accounting for 74% of the total abandoned area. In 2006, recultivation peaked with 1475 × 10^3 ha of land, while 2003 saw the least at about 190 × 10^3 ha (Figure 3-13(c)).

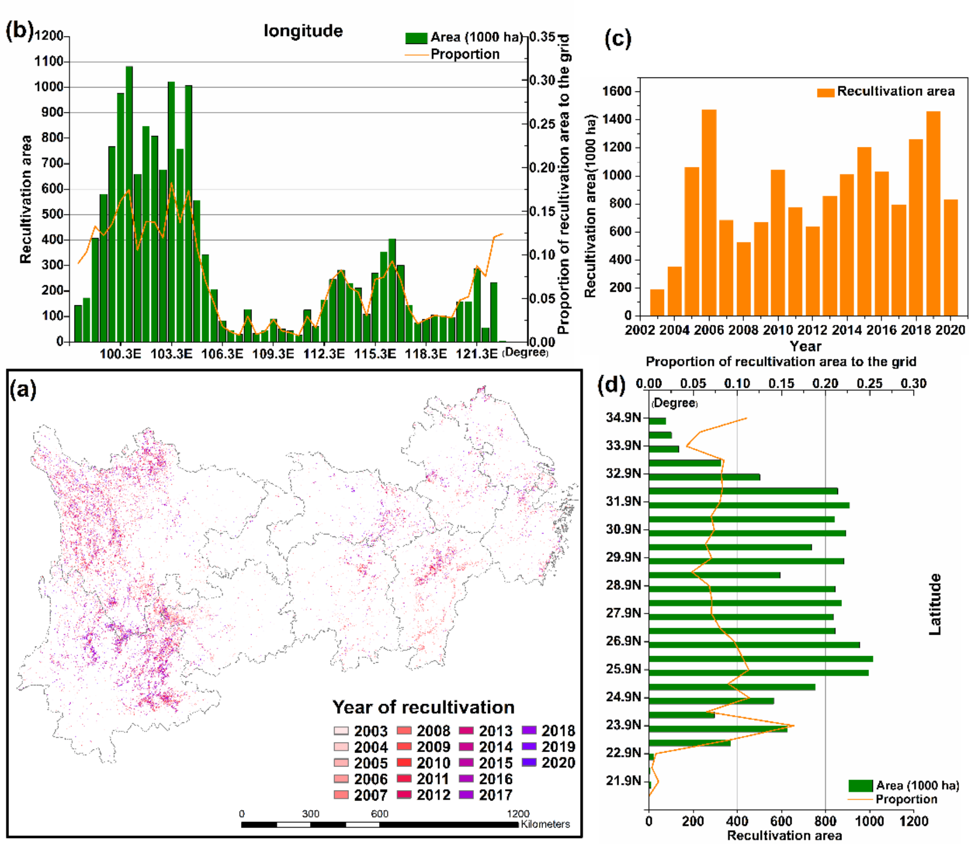

Figure 3-13. The spatiotemporal pattern of cropland recultivation from 2003 to 2020 across the Yangtze River basin. (a) The spatiotemporal pattern of recultivation from 2003 to 2020. (b,d) Accumulated recultivation area (green bar) along longitudinal and latitudinal gradients (0.5°). The orange line represents proportion of recultivation area as compared to the total land area. (c) Annual reculti-vation area (10^3 ha).

4. Discussion

This study mapped the spatiotemporal dynamics of cropland abandonment and recultivation across the Yangtze River basin. Compared to previous macro-analyses with a particular focused on China, this study offers an in-depth understanding of the spatiotemporal interplay between abandonment and recultivation. The outcomes provide policymakers with new insights that can be used to develop a balanced policy-making strategy which aims at optimizing the balance between agricultural productivity on the one hand and ecological conservation on the other hand. As such, it offers a scientific basis to improve the management of abandoned croplands considering the unique environmental land socio-economical context of the Yangtze River basin. Additionally, the novel methodology and insights from this study may serve as a model for analogous research in other regions, contributing to the development of sustainable land management strategies.

4.1. Comparison with other studies

Due to the significant interannual variability in the cropland spectrum, mapping abandoned land via cropland dynamic maps is challenging (Prishchepov et al., 2012a). An overall land use classification accuracy of 0.82–0.85 was achieved through the rapid collection of high-precision samples. Recent studies on mapping abandoned cropland in China achieved a land use classification accuracy exceeding 0.75, with classification accuracies of more than 86% for some large-scale areas (Jiang et al., 2023; Zhu et al., 2021), which is similar to our results, and as such the efficacy of our classification method and its suitability for cropland abandonment detection is comparable. However, the average F1 score for our cropland classification was 0.84 (Figure 3-7), slightly lower than that in the study by (He et al., 2022), potentially due to the lower resolution of data used in our study compared to theirs.

The comparative analysis reveals both similarities and differences in the definitions of abandonment in these studies. A consensus is the cessation of agricultural activities and management, which is recognized in all studies. This definition leads to different potential outcomes, ranging from ecological impacts (Rodrigo-Comino et al., 2018) to land use changes (Ustaoglu and Collier, 2018), which reflects a different research focus concerning the process of land abandonment, i.e., considering either (i) the transitional nature and potential outcomes or (ii) the associated policy implications and opportunities. However, some studies consider both, recognizing the complex and multifaceted nature of abandonment (Fayet et al., 2022a; Fayet et al., 2022b). Our research adds a specific, measurable definition to this spectrum, enriching the understanding of land abandonment from a temporal and ecological perspective.

Notably, the current study found that at least 19% of cropland in China has been abandoned at least once (ranging from 19% to 28%) (Han and Song, 2019; Jiang et al., 2023; Zhang et al., 2023a). Compared to our study, this proportion is slightly lower, i.e., 30%. This difference may be related to the length of the study and the methodology. For instance, Li et al. (2018) estimated the extent of abandoned cropland across mountain areas based on household survey data. Their results showed that the abandonment rate of cropland in mountainous areas was about 28% during 2000–2010, including during the Grain for Green Program. This value is notably higher than our findings (i.e., 13%), which is not a surprise as Li et al. (2018) also included afforestation, which is not the case in the present study. Similarly, Xu et al. (2019a) used data from the China Household Finance Survey (CHFS) to conduct household surveys across 29 out of 34 provinces of China, finding that the abandonment rate of cropland in 2011 and 2013 was 13% and 15%, respectively, which is similar to our findings. In a global context, the abandonment proportion in the Yangtze River basin aligns with figures from Eastern Europe, the former Soviet Union, and Chile (16% to 42%) (Dara et al., 2018; Díaz et al., 2011; Prishchepov et al., 2012a), but is higher than those reported for Central Asia (approximately 13%) (Löw et al., 2018).

Our abandonment durations were much shorter than the global average, i.e.14 years reported by(Crawford et al., 2022), but our abandonment duration was similar to Song (2019) (i.e. 3.5 years). At the same time, studies in the tropics have shown that the duration of secondary forest recultivation is usually short (Chazdon et al., 2016; Nunes et al., 2020; Schwartz et al., 2020; Smith et al., 2020). In the Brazilian Amazon, secondary forests are cleared and recultivated much more rapidly (50% within 5 to 8 years), resulting in 80% of secondary forests being ≤20 years old. In contrast, across the tropics, only 33% of forests that had been regenerated on recently cleared sites were ≥10 years old.

However, it is important to emphasize that caution is needed when directly comparing these regions. Variations in the definitions of "cropland abandonment" across studies can impact the comparability of these rates. For instance, one study in China estimated that the area of cropland abandonment for five years accounted for 19% of China's total cropland (Zhang et al., 2023a). However, this definition ignores different farming systems across different regions, and, therefore, may result in a misclassification of short-term cropland abandonment (i.e., non-fallow), and as such underestimate the area of abandonment. Another study in Central Asia, which defined abandonment as three consecutive years of non-use of cropland, estimated that abandonment in northern Kazakhstan is equal to 40.5% (Dara et al., 2018), a figure which is higher than that presented by our results. However, one study used the same definition, but found the proportion of abandoned areas in the Guizhou–Guangxi karst mountain area of China to be around 16%, which is lower than our findings (Han and Song, 2019).

4.2. Cropland abandonment and recultivation drivers

Cropland abandonment across the Yangtze River basin became progressively more apparent at the beginning of this century, although there were annual and regional variations. The implementation of the Rural Land Contracting Law and the abolition of agricultural taxes in 2006 might lead to restricted areas of abandonment across our study area (Figure 3-9(c)) (Wang and Shen, 2014). The shift away from agriculture, induced by increasing farming costs and the appeal of non-agricultural sectors, was especially noticeable near urban areas in the Yangtze River delta region (Figure 3-9(a,b)). Similar trends have been observed in parts of Western Europe and America (Hou et al., 2021; Levers et al., 2018; Long et al., 2018; Rigg et al., 2018).

Our research has identified a notable increase in recultivation, a trend that has become increasingly prominent over time (Figure S4). This phenomenon potentially elucidates the observed, albeit statistically non-significant, decline in both the extent of cropland abandonment and its corresponding rate (Figure S3). Concurrently, this trend underlines the extensive adoption of recultivation policies strategically aimed at diminishing potential food security threats. As the decade progressed into the mid-2000s, a transition towards the recultivation of previously abandoned croplands began to emerge. This shift was mainly influenced by policy adjustments, particularly the reduction in GGP subsidies, motivating farmers, especially those enrolled before 2007, to reengage with their initial agricultural activities, and, therefore, recultivate their lands (Zhang et al., 2017). Governmental directives in 2004 and 2014, focusing on food security (e.g., Emergency Circular on Restoring Abandoned Cropland Production), further fueled the recultivation momentum in our area. In addition, The policy National Land Consolidation and Rehabilitation Plan (2011–2015) aimed to counteract abandonment by consolidating fragmented cropland and modernizing infrastructure in mountainous areas (Long et al., 2022), which resulted in a noticeable decrease in the abandonment rate.

Concurrent socio–economic upheavals, like the economic crises of 2008, resulting in urban unemployment, prompted a rural return (Cai and Chan, 2013; Huang et al., 2011), aligning with the observed increase in recultivation area during this period (Figure 3-13(c)). Additionally, region-specific agricultural strategies, such as the minimum purchase price for grain products in provinces like Jiangxi, Anhui, and Jiangsu, contributed to the post-2009 surge in recultivation (Li et al., 2021b; Liu et al., 2020c).

When looking to the absolute total cropland abandonment areas, slopes less than 5° have been characterized by the largest abandonment area (Figure 3-14(a)), e.g., ranging between 192 × 10^3 ha and 852 × 10^3 ha from 2002 to 2020. However, when considering RCAP (Figure 3-14(b)), this increases with increasing slope steepness, reaching a maximum value of 11% for slopes of 20–25° in the year 2005. Soil degradation processes on these steeper slopes, mainly due to soil erosion, leads to higher management costs and reduced crop yields (Zhang et al., 2018). Furthermore, in mountainous areas, greater distances between homes and croplands increases the likelihood of abandonment, particularly on steeper terrains (Shi et al., 2016; Subedi et al., 2022). While GGP was not the focus of this study, the increased wildlife crop raiding associated with forest expansion due to GGP could raise production costs (Xu et al., 2019b). This may be another major reason for cropland abandonment in mountainous areas.

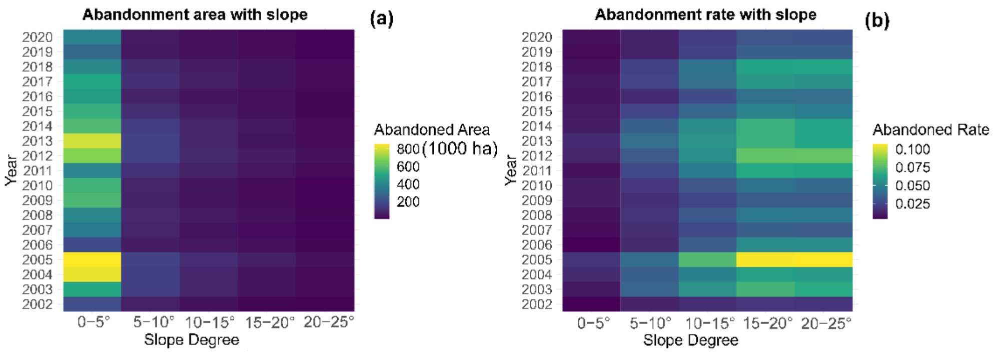

Figure 3-14. Temporal distribution in (a) total cropland abandonment area (absolute values) and (b) RCAP based on terrain differences. X axes show different slope ranges (0−5°, 5−10°,

10−15°, 15−20°, 20−25°), Y axes show different years covered by our study period. Slopes above 25° are not considered in order to excludes GGP's impacts.

5. Conclusion

Cropland abandonment is of wide concern in China as it may endanger the nation's food security. Using MODIS data on the GEE platform, we employed the RF algorithm to map LULC across the Yangtze River basin from 2000 to 2020. Additionally, we undertook spatial–temporal analyses to assess spatiotemporal interactions between cropland abandonment and recultivation.

Our LULC maps achieved an accuracy ranging between 0.82 and 0.85 throughout the study period. We observed widespread cropland abandonment, particularly in areas with slopes under 5°, but overall rates remained low. Abandonment was most notable in Sichuan, Yunnan, and specific urbanized areas in the East. The total abandoned cropland covered an area of 21,490 × 10^3 ha, with yearly fluctuations (e.g., a maximum of 2104 × 10^3 ha in 2005 and a minimum value of 526 × 10^3 ha in 2002). By 2020, 15,857 × 10^3 ha (or 74% of total abandoned area) had been recultivated, reflecting that cropland abandonment in the basin occurs less frequently and for shorter durations (about 5.5 years on average). Changing agricultural policies, economic dynamics, and increased urbanization and food needs led to more than half of the abandoned cropland being recultivated within the timespan of three years.

This study highlights the dynamic nature of land use within agriculture landscapes and the urgent need for long-term high-resolution regular monitoring. The pre-sent methodology and the resulting maps of cropland abandonment provide the basis for a balanced policy considering both ecological conservation and food security. Abandoned cropland can be a promising avenue for unlocking additional land re-sources in a world where land scarcity remains a major hindrance to sustainable development. The potential benefits of strategically recultivating abandoned cropland and/or reforesting it are in line with global initiatives such as the Paris Agreement and the United Nations' Sustainable Development Goals (SDGs), particularly Zero Hunger (SDG 2) and Life on Land (SDG 15), which focus on restoring degraded land and in-creasing afforestation. Therefore, we identified a future research direction that explores the trade-offs and potential benefits between different uses of abandoned cropland. This direction is particularly important for understanding the synergistic effects of land use decisions on climate goals and sustainable development.

6. Supplementary information

All supplementary information mentioned in this chapter is publicly available on the published paper's webpage at:
https://www.mdpi.com/article/10.3390/rs16061052

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Chapter 4

Tradeoffs of cropland abandonment for food and carbon

This chapter is based on:
Long, Y., Sun, J., Peng, J., Wellens, J., Colinet, G., Wu, W & Meersmans, J. (2024). Tradeoffs between climate change mitigation and food security following cropland abandonment and recultivation in Central China (Yangtze River Basin). (In preparation)

Abstract

Cropland abandonment and recultivation are complex land use changes in the Yangtze River Basin. The interaction between cropland abandonment and recultivation provide significant benefits for climate change mitigation. However, balancing climate change mitigation with food security presents challenges and opportunities for landscape managers and policy makers to optimise ecosystem services. In our study, we mapped cropland abandonment and recultivation patterns in the Yangtze River Basin. In this context, two key ecosystem services, carbon stock change and grain yield change, were estimated for each province. Finally, we assessed the trade-offs and synergies between changes in carbon stocks and grain yields at the provincial and grid levels. The results show that cropland abandonment and recultivation of cropland are widespread and intersect in the Yangtze River Basin provinces from 2002 to 2020. The growth of cropland abandonment area plays a positive role in carbon stock changes, accumulating 182.3 Mtons of carbon, which is 48.1% of the scenario accumulation without recultivation. Despite the recultivation of region, cropland abandonment still resulted in a cumulative reduction of 13.47 Mtons of grain production. Using Spearman correlation analysis, we find a significant trade-off between changes in carbon stocks and grain production at the provincial scale ($r<0$, $p<0.05$). Specifically, we observe differences in the spatial distribution of trade-off and synergy. For example, Hunan clearly shows areas where the trade-off relationship is weak and areas where the synergistic relationship crosses over. This study deepens the understanding of the trade-offs between changes in carbon stocks and changes in food production during abandonment and restoration, and provides insights for adjusting restoration programmes to simultaneously achieve climate change mitigation and food security objectives.

1. Introduction

The persistent global climate warming is an undeniable reality, exerting detrimental effects on the growth environment of crops worldwide. This phenomenon has led to a notable decrease in the yields of key agricultural products like maize, with an anticipated reduction of 24% by the late century under high greenhouse gas emissions scenarios (Jagermeyr et al., 2021; Lobell et al., 2011; Zhu et al., 2022). Alarmingly, the number of people grappling with acute food insecurity has soared to 828 million in 2021, reflecting a sharp increase (FAO, 2022). Despite advancements in agricultural intensification potentially mitigating the need for expanded cropland (Zabel et al., 2019) , the continuous surge in population and per capita food consumption suggests that cropland expansion is inevitable. The Shared Socioeconomic Pathways (SSPs) framework projects a significant increase in global cropland, ranging from 25 to 226 million hectares in the next three decades (Popp et al., 2017; Riahi et al., 2017). However, this indiscriminate expansion in certain geographical regions threatens to destabilize terrestrial ecosystems, underscoring the critical need for strategic land management to preserve ecological balance (Paz et al., 2020; Ray et al., 2022).

Agricultural production is a significant source of global greenhouse gas (GHG) emissions, contributing substantially to climate change. This sector and land-use change, accounts for approximately a quarter of total global emissions, with food systems responsible for around one-third of these emissions (Clark et al., 2020; Laborde et al., 2021). Reducing emissions in agriculture, especially from fossil fuels and soil disturbance, is crucial for achieving net-zero carbon emissions. Nature-based solutions (NBS), such as carbon sequestration in grasslands and forests, are projected to reduce up to 30% of carbon emissions by 2050 (Roe et al., 2019). These solutions emphasize land conservation, restoration, and management practices aimed at reducing emissions. However, implementing these climate change mitigation measures on a large scale, necessary to limit global warming to below 2°C, requires extensive nature vegetation land use. This requirement poses a potential conflict with future agricultural land expansion and food production (Gvein et al., 2023; Strassburg et al., 2020). The clash between climate change mitigation measures and agricultural needs underscores the complexity of balancing environmental sustainability with food security and land use (Fujimori et al., 2022).

Globally, agricultural land abandonment is a widespread phenomenon. It is estimated that between 2003 and 2019, around 79 million hectares (Mha) of cropland were abandoned worldwide, with significant abandonment occurring in Europe, Central Asia, Russia, and China (Potapov et al., 2022). These regions are expected to continue experiencing high rates of abandonment (Crawford et al., 2022; Zheng et al., 2023). While cropland abandonment can enhance soil carbon storage and mitigate the adverse impacts of agriculture on biodiversity and ecosystem services, it presents substantial trade-offs, particularly in the context of escalating food demands. The long-term abandonment of cropland poses risks to local food security, especially in subsistence and smallholder farming systems with limited market access (Baiphethi and Jacobs, 2009; Blair et al., 2018). In regions like China, recent policies have been advocating for the optimization of abandoned croplands that are suitable for production, aiming to ensure future food security (e.g., Emergency Circular on Restoring Abandoned Cropland Production, http://f.mnr.gov.cn/201702/t20170206_1436285.html). Considering these concerns, assessing the trade-offs and synergies between climate change mitigation and food security from abandoned cropland and recultivation is vital in designing and evaluating restoration strategies.

The complex intercation between cropland abandonment, climate change mitigation, and food security presents significant challenges. Recent studies highlight a substantial gap in understanding how abandoned cropland can support both climate change mitigation and food security, with a notable lack of assessment on the trade-offs and synergistic effects among various ecosystem services of these lands (Dade et al., 2019). Evaluating these services is essential for informed land u se decision-making, although the objectives for land use may not always align with assessment outcomes This complexity is further exemplified in the trade-off between carbon sequestration and grain production, which illustrates the need to balance ecological benefits against agricultural productivity (Qiu et al., 2021; Rimal et al., 2019; Zhong et al., 2020). At the same time, the spatial variability in the duration of cropland abandonment, understanding the duration of abandoned cropland is critical to understanding its ability to influence the current climate change and food crisis (Daskalova and Kamp, 2023) . However, this persistent issue has received scant attention from researchers. A critical challenge in this domain is the issue of scale consistency, as food production is often discussed at a city or regional level, while carbon sequestration is considered at national or international scales, creating difficulties in effectively quantifying trade-offs and synergies (Peng et al., 2017). Addressing this challenge calls for research that incorporates both spatiotemporal scales and focuses on optimizing benefits at more finer levels, like grid scale (Tilman et al., 2011; West et al., 2010). Given these complexities, there is an urgent need for more targeted research on the abandoned cropland on ecosystem services and call for better quantification and optimisation of trade-offs and synergies for abandoned cropland management strategy.

Carbon stock change is used as an indicator for measuring climate change mitigation, and food supply (e.g. grain yield change) is the most common indicator of food security (Mackey et al., 2013; Nicholson et al., 2021). Here, we assess the impacts and trade-offs of abandoned cropland in the Yangtze River Basin for food security and climate change mitigation based on geospatial modelling, machine learning. Our study seeks to answer the following questions:

(1) What is the magnitude and persistence of cropland abandonment and recultivation across the 11 provinces in our study region?

(2) How do carbon stock change and grain yield change patterns distribution following cropland abandonment?

(3) What is the tradeoff or synergy relationship between carbon stock change and grain yield change in the both province and grid level?

Unraveling these dynamics is pivotal, not just for the Yangtze River Basin, but as a model for understanding similar challenges globally. By exploring the interplay between carbon stock change and grain production change, our findings can inform sustainable land use policies that effectively address both climate change mitigation and food security concerns.

2. Material and methods

2.1. Study area

The Yangtze River Basin is an extremely important ecological carrying area, agricultural production area, and economic development area in China, and it is a macroeconomic coordinated belt of giant river basins with the largest population and industrial scale and the most complete urban system in the world (Figure 4-1). However, the socio-economic and agricultural technological foundations of the Yangtze River Basin, such as the proportion of high-quality cropland, the construction of water conservancy projects, and the level of agricultural mechanization, are weak, which has led to a series of problems such as the abandonment of cropland (Guo et al., 2021; Qi et al., 2021). With the development of the economy and the improvement of transport conditions, the impact of changes in the form of cropland use on the land ecological environment and has become more and more prominent, seriously restricting the development, utilization and production of land resources in the region. Therefore, in such a context, it is crucial to clarify the impacts and trade-offs of abandoned land on the ecological environment and agricultural production across the Yangtze River Basin.

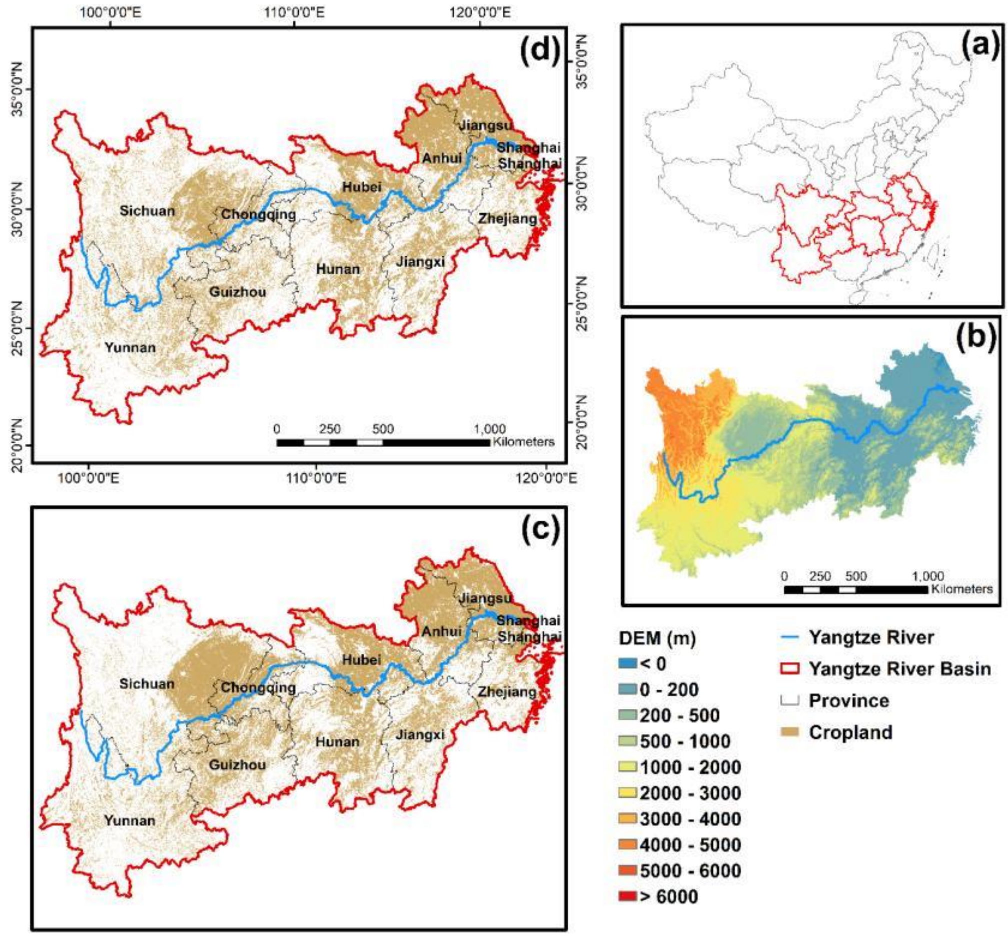

Figure 4-1. Geographical location of study area. (a) Location of the Yangtze River Basin; (b) Digital Elevation Model (DEM) across the Yangtze River Basin; (c) and (d) The spatial pattern of cropland in 2000 and 2020.

2.2. Data processing

Our detailed study flowchart could be seen in Figure 4-2. Initially, we utilized time series data from MODIS-NDVI to classify land use types and identify areas of cropland abandonment and recultivation, aligning with our predefined criteria for land abandonment. Concurrently, NDVI data can be used as a base map for spatialisation of provincial food production statistics. This step facilitated the calculation of grain yield change in the context of abandonment and recultivation processes, primarily conducted using Google Earth Engine (GEE) and ArcGIS 10.2 ESRI (Environmental Systems Research Institute, 2013). Subsequently, the classified land use data and carbon pools information were input into the InVEST model (Integrated Valuation of Ecosystem Services and Tradeoffs) to calculate carbon stock at the pixel level. This process allowed us to assess the changes in carbon storage associated with the patterns of land abandonment and recultivation. Finally, we computed the correlation coefficients and p-values for the carbon stock change and grain yield change at both the provincial scale and on a 10km grid scale using R (Version: 4.3.1). This statistical analysis was pivotal in evaluating the trade-offs and synergies between carbon storage and agricultural productivity. The administrative boundaries are from the Geographical Information Monitoring Cloud Platform [http://www.dsac.cn, accessed on 1 December 2022].

Our data pre-processing was methodically executed in several stages. Initially, we focused on reconstructing NDVI profiles to accurately represent the true NDVI and minimize error. For this purpose, we applied the Whittaker Smoother algorithm to each year of the time series, a technique known for its efficacy in demonstrating phenology metrics (Atzberger and Eilers, 2011a; Kong et al., 2019; Shao et al., 2016). Subsequently, we focused on collecting and calculating baseline carbon pools for different land use types (e.g. cropland, grassland and forest). This dataset was derived from sources including the Intergovernmental Panel on Climate Change (IPCC) and other literatures. To ensure a robust analysis, we calibrated the carbon pools data using meteorological station data [http://data.cma.cn/en, accessed on 1 December 2022] (Supplementary Information 2.2). Finally, we collected agricultural statistics for 11 provinces from 2000-2020 (China Statistical Yearbook, NBSC, 2000 to 2020). Our focus was on six main crops—rice, wheat, maize, soybean, potato, and rape—which are predominantly grown in the Yangtze River Basin(Guo et al., 2021; Wang et al., 2023).

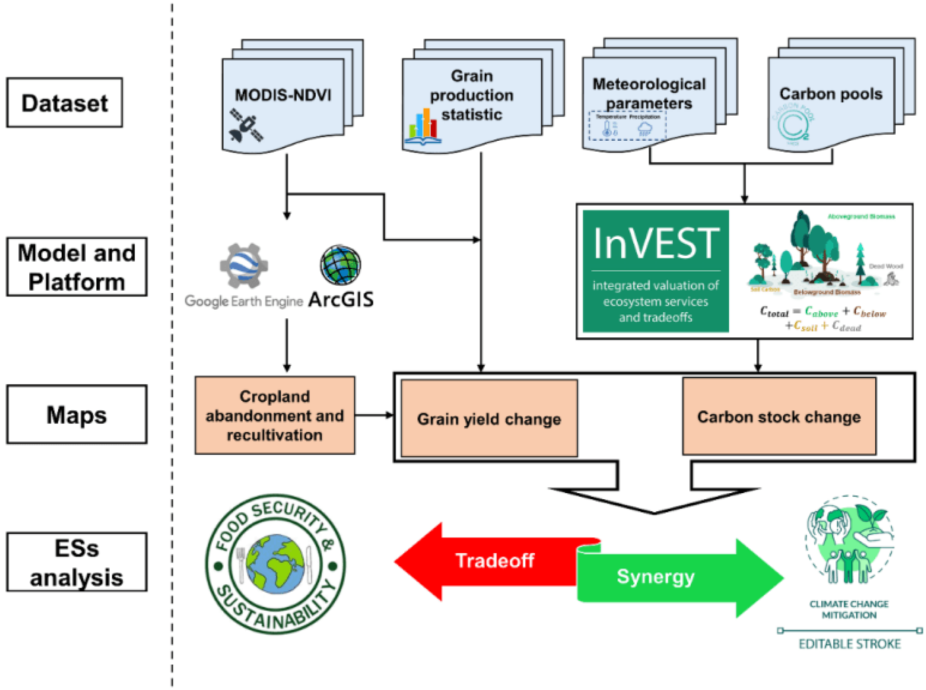

Figure 4-2. Flowchart of study.

2.3. Mapping abandoned cropland and recultivation

We used annual land cover maps at 30 m resolution from 2000 to 2020 derived from publicly available MODIS satellite imagery using a random forest algorithm to map eight land cover classes: cropland, grassland, forest, shrub, bareland, impervious surfaces, wetland, and water (Figure 3-4).

We produced maps with high accuracy (average overall accuracy of 0.82-0.85), with differences in F1 values for different land cover. Land cover specific F1 scores were highest for forest (0.90 ± 0.01), followed by water (0.89 ± 0.02), cropland (0.84 ± 0.01), grassland (0.84 ± 0.01), and impervious surface (0.83 ± 0.03). Significantly lower F1 scores were observed for wetland (0.41 ± 0.1) and shrubs (0.47 ± 0.03) (Figure 3-6 and 3-7).

We selected our study areas to analyze abandonment and recultivation across the Yangtze River Basin. Here, we use spatiotemporal dynamic of cropland abandonment and recultivation originally mapped by Long et al. (2024). Although, our study sites are not representative of abandonment in China as a whole, they are likely representative of those areas that have recently experienced abandonment, and present a unique opportunity to understand the issue of abandonment.

2.4. Modelling carbon stock change and grain yield change

2.4.1. Carbon stock change estimation

The InVEST carbon sequestration module, known for its efficiency and accuracy, has been widely used to estimate and map carbon stock. It offers a less labor-intensive approach, with the additional benefits of independent verification and open-source accessibility (Jiang et al., 2021). The module assesses carbon stock in two main components: soil and plants, the latter including both above- and below-ground parts such as shoots and roots. It evaluates four primary terrestrial carbon sinks: aboveground and belowground biomass, soil organic carbon, and humus carbon in different land cover. Carbon pool data in each land cover often remained unchanged over time when estimating carbon emission and/or sequestration due to land use change (Hernández-Guzmán et al., 2019; Poeplau and Don, 2013). In our study, we collected provincial carbon pool data from literatures and corrected with meteorological data. We then calculated the average carbon pool data of each land cover from 2000 to 2020 as the input value for the module (Table S1 and S3-S13).

$$C_{total} = C_{above} + C_{below} + C_{Soil} + C_{dead} \quad (1)$$

Where, C_{total}, C_{above}, C_{soil} and C_{dead} represent total of carbon stock (TOC, ton/ha), aboveground biomass (ton/ha), below biomass (ton/ha), soil organic carbon (SOC, ton/ha), and humus carbon (ton/ha), respectively. It is challenge to obtain humus carbon, and it can be ignored (Lehmann and Kleber, 2015; Sharp et al., 2016).

We employed IPCC Tier Guidelines and referred to recent research on annual carbon sequestration rates during secondary succession. The time series of carbon stock change was divided into two stages: land cover change and nature regeneration. During the land cover change phase, we used equation (2) to detail the annual carbon stock change as cropland transitions to natural vegetation (IPCC, 2003, 2019). For the nature regeneration phase, we calculated Total Organic Carbon (TOC) sequestration from the point of abandonment until recultivation or the end of our 19-year study period. We assumed a constant carbon sequestration rate of 2.38 tons/ha/yr for most vegetation types, validated by conditions in China (Cook-Patton et al., 2020). Soil carbon stock changes were measured using data from the Soils Revealed database (Sanderman et al., 2023).

$$\Delta C_{stock} = (C_j - C_i)/T_{ij} \quad (2)$$

Where, ΔC_{stock} , C_j and C_i indicate annual change in carbon stock change (ton/ha/yr), carbon stock of current land cover j (ton/ha) and carbon stock of previous land cover i (ton/ha). T_{ij} is time period of the transition from state i to state j (yr), the default is 20 years.

2.4.2. Pixel-based grain yield change estimation

To calculate pixel-level grain production in croplands, we utilized annual grain production statistics (China Statistical Yearbook, NBSC, 2000 to 2020) along with remote sensing data. We specifically utilized a multi-temporal NDVI imagery time series. In this study, we spatially downscaled the grain production from the provincial level to the pixel level. This was done using the following formula, based on the internally normalized differential vegetation index (NDVI) of cropland for each province, next to convert the grain production into yield (equation 3-4), and finally to calculate the inter-annual grain yield difference:

$$G_{ij} = \frac{NDVI_{i,j}}{NDVI_{sum,j}} \times G_j \tag{3}$$

$$Y_{ij} = \frac{G_{ij}}{Area} \tag{4}$$

Where, i represents the pixel of the cropland layer in the province j. G_{ij} indicates grain production allocated by the pixel i of cropland in the province j (ton). G_j indicates total grain production of cropland in the province j. $NDVI_{ij}$ indicates the NDVI value allocated by the pixel i of cropland in the province j, and $NDVI_{sum,j}$ represents the sum value of cropland NDVI in the province j. Y_{ij} represent grain yield allocated by the pixel i of cropland in the province j (ton/ha). In our study, one pixel $Area$ = 6.25 ha.

2.5. *Trade-off Analysis*

In the context of the intricate interaction between land abandonment and recultivation, we investigate the correlation between changes in carbon stocks and shifts in grain yields at both provincial and grid scales. This method allows for a continuous temporal assessment of ecosystem services, creating spatially explicit maps to elucidate their interconnections. Without employing this methodology, the accurate measurement of ecosystem responses to external factors, such as time-lag effects, becomes challenging. This can lead to potential misinterpretations of the temporal variability in data (Tomscha and Gergel, 2016). By integrating spatial mapping with diverse data sources, we gain a comprehensive understanding of the spatial changes in ecosystem services, thereby facilitating informed decision-making for ecological conservation (Zhang et al., 2016).

To discern the relationship between carbon storage and food production, we analyzed the spatial overlaps of ecosystem services from 2000 to 2020 at a 10km grid level. We computed the standard ecosystem service as per the approach outlined by Bradford and D'Amato (2012), thereby normalizing unit effects for each ecosystem service before conducting the correlation analysis.

$$X_i' = \frac{X_i - X_{min}}{X_{max} - X_{min}} \tag{5}$$

Where X_i' is the normalized value of the indicator, X_i is the value of the indicator for each ecosystem services, and X_{min} and X_{max} are the minimum and maximum value of each considered indicator variable over the production situations, respectively.

To initially identify the positive and negative relationships in a given region, we used Spearman correlation analysis (Cord et al., 2017; Kalfas et al., 2019). The rationale for selecting Spearman correlation is detailed in Supplementary Information 4. A significantly positive correlation between two ecosystem services (r_{ij}>0, p_{ij} < 0.05) indicates synergy, where multiple ecosystem services change in the same direction, whether increasing or decreasing. In cases of 'positive synergy', both services are increasing, whereas in 'negative synergy', both services are decreasing. Conversely, a significantly negative correlation (r_{ij}<0, p_{ij} < 0.05) indicates a trade-off between the two services, where multiple ecosystem services change in the opposite direction.

$$r_{ij} = \frac{\sum(x_{ij} - \bar{x}_{ij})(y_{ij} - \bar{y}_{ij})}{\sqrt{\sum(x_{ij} - \bar{x}_{ij})^2} \times \sqrt{\sum(y_{ij} - \bar{y}_{ij})^2}} \tag{6}$$

$$p_{ij} = \frac{r_{ij}}{\sqrt{\frac{1 - {r_{ij}}^2}{n - 2}}} \tag{7}$$

Where, r_{ij} represents correlation coefficient in i pixel in the j year. x_{ij} and y_{ij} indicate two ecosystem services by the i pixel in the j year. p_{ij} indicates determining the significance of interrelationships between ecosystem services based on the null hypothesis test t-test of correlation coefficients. n represents number of observations.

3. Results

3.1. Maps of abandoned croplands and loss extent in each province

Cropland abandonment was widespread across our 11 study regions. We discovered that during 2002-2020, approximately 21490×10³ ha of croplands were abandoned (Figure 4-3(a)). In individual regions, the abandoned cropland area varies, comprising 0.3% (Shanghai) to 49% (Sichuan) of the total cropland extent. The majority of abandoned land in Sichuan is situated in the north-western and southern mountainous regions. Similarly, in Yunnan and Guizhou, abandoned croplands are predominantly found in the eastern and western regions, respectively, sharing geographical similarities with Sichuan. Additionally, in regions like Hubei and Jiangxi, abandoned croplands were notably observed near urban areas.

Despite widespread abandonment, a substantial proportion of these lands underwent change again, either through recultivation or conversion into other land covers. A striking finding was that by 2020, nearly 74% of the abandoned croplands had experienced at least one recultivation (Figure 4-3(b)). Simultaneously, urbanization claimed about 7% of the abandoned croplands, transforming them into impervious surfaces (Figure 4-3(c)). On average, 73% (SD = 8%) of abandoned croplands in each province were recultivated (Figure 3-13). Additionally, 14% (SD = 8%) of abandoned croplands in each province, on average, were converted to other impervious surfaces (Figure S1). By 2020, only 4027 ×10³ ha of croplands remained abandoned across our study regions, an 81% reduction from the area abandoned at least once during the time series. This represents the potential area that could have been abandoned in 2020 without recultivation or other conversions. The extent of cropland abandonment varied by province (Figure 4-3(d)), with abandoned croplands in 2020 occupying between 63% (Jiangsu) and 87% (Guizhou) less area compared to the potential area without recultivation and other conversions. The conversion of abandoned croplands to impervious surfaces also varied by province, with abandoned cropland areas being 4% (Sichuan) to 27% (Zhejiang) less compared to potential lands without any loss by 2020.

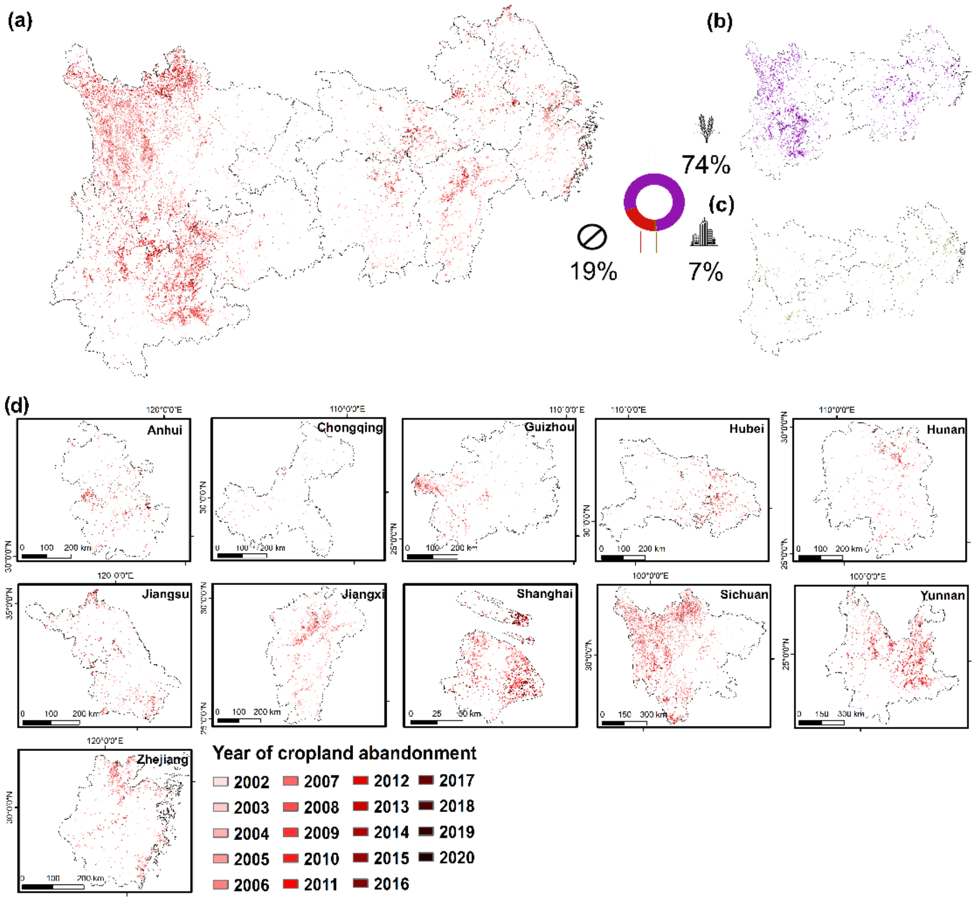

Figure 4-3. (a) Overall a bandoned cropland extent and abandoned croplands loss for (b) recultivation and (c) impervious surfaces. Proportions (donut chart) and spatial distribution (maps) of three conversion of abandoned cropland: recultivation (74%), impervious surfaces (7%) or remaining abandonment until 2020 (19%). (d) Abandoned cropland extent in each province (Long et al., 2024).

3.2. Abandonment duration distribution at each province

In this study define 'real abandonment durations' is defined as the average duration obsered on the succesive maps of cropland abandonmet (fig 4-3), whereas 'scenario abandonment durations' refer to the hypothetical durations if no recultivation or other conversions would have taken place. Due to recultivation and other conversions, the real duration of abandonment across all provinces was brief. This was documented in Chapter 3 (Long et al., 2024), which found that the average duration was 3.2 years

(SD = 1.7), with a range from 2.0 years (Chongqing) to 8.1 years (Sichuan) (Figure 4-4). For comparison, the real abandonment durations were significantly shorter than the scenario durations, i.e. 11.7 years (SD = 1.2) on average—ranging from 9.3 years (Hubei) to 14.0 years (Guizhou) (Figure S2). The real abandonment duration varied considerably within provinces, with a standard deviation ranging from 1.7 years (Shanghai) to 5.1 years (Sichuan), averaging 2.7 years across all provinces. Notably, short-term abandonment (less than 3 years) was prevalent in each province. With the exception of Sichuan and Yunnan, over 70% of the abandoned areas across all provinces experienced short-term abandonment.

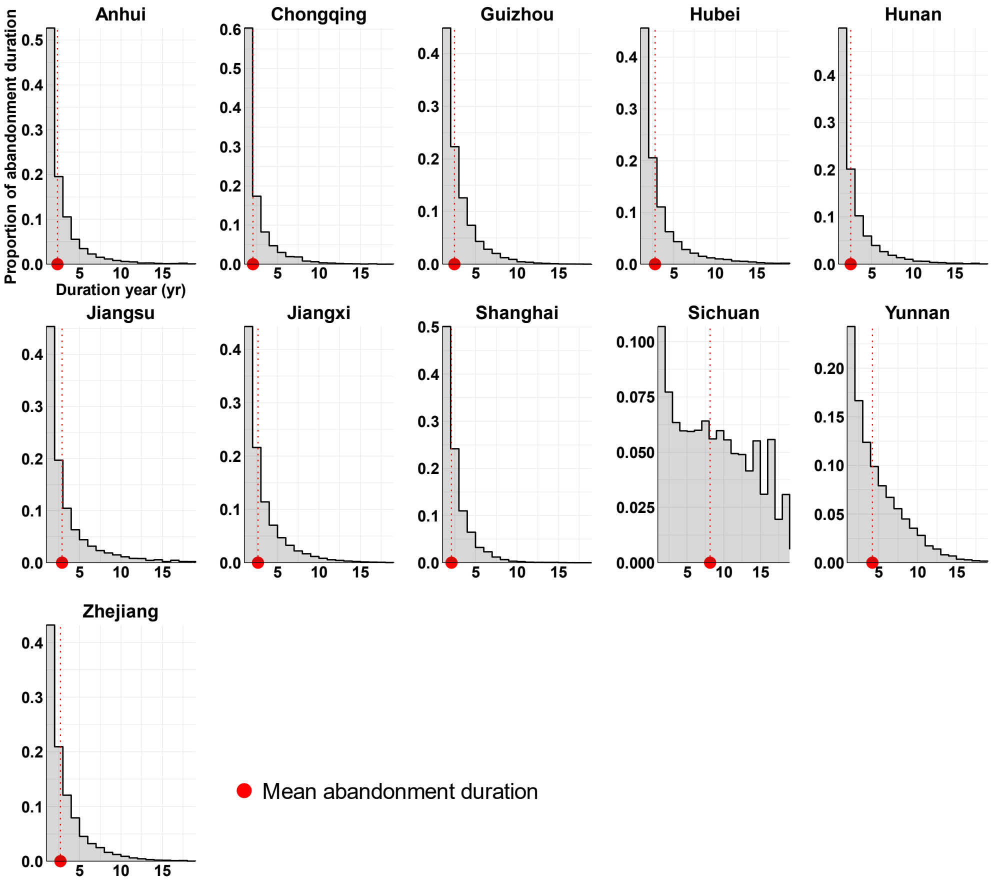

Figure 4-4. Distribution of ‘real abandonment duration’ through time. The distribution of abandonment duration (in years) for all periods of abandonment from 2002 to 2020. The y axes show the proportion of abandonment area of a given duration at each province. The red points and vertical dashed line represent the mean abandonment duration (in years) at each province. Note that these distributions include multiple periods of abandonment for those pixels that experienced abandonment multiple times during the studied period.

3.3. Annual carbon stock change and grain yield change maps

We evaluated changes in carbon stock and accumulation in abandoned croplands by using global maps indicating potential changes in vegetation succession carbon stock and soil organic carbon during the natural regrowth of native vegetation (Cook-Patton et al., 2020; IPCC, 2003, 2019; Sanderman et al., 2023), taking into account the duration of abandonment. The study area exhibits a positive carbon stock change rate, with the average value ranging from 0.04 tons/ha/yr (Shanghai) to 1.1 tons/ha/yr (Sichuan)(Figure 4-5 and Table 4-1). By 2020, an estimated total of 182.3 Mton C did accumulate across the 11 provinces, a figure 51.9% lower than the scenario accumulation of 379.2 Mton C, had there been no recultivation or conversions (Figure S4). The reductions in estimated carbon accumulation due to recultivation and other conversions ranged from 24.9% (Sichuan) to 95.6% (Shanghai) across provinces.

Recultivating abandoned croplands is essential for addressing food insecurity, yet the change in grain yield varies significantly across provinces (Figure 4-6 and Table 4-1). For instance, Jiangsu experienced a decrease of -0.08 ton/ha/yr, while Jiangxi and Guizhou showed a slight increase of 0.02 ton/ha/yr and 0.01 ton/ha/yr, respectively. This can be partially attributed to differences in the proportion of croplands recultivated between provinces. By 2020, Guizhou and Jiangxi had achieved a recultivation proportion of over 80%. Similarly, we estimated a reduction of 13.47 Mtons in grain production across our 11 provinces by 2020 (Figure S5). While Jiangxi and Guizhou experienced increases in grain production, other regions saw reductions, ranging from -0.05 Mtons in Chongqing to -10.27 Mtons in Sichuan. When we do not consider the recultivation scenario, the cumulative reduction in grain production improves by almost four times to 65.64 Mtons, ranging from -0.19 Mtons in Chongqing to 30.34 Mton in Sichuan.

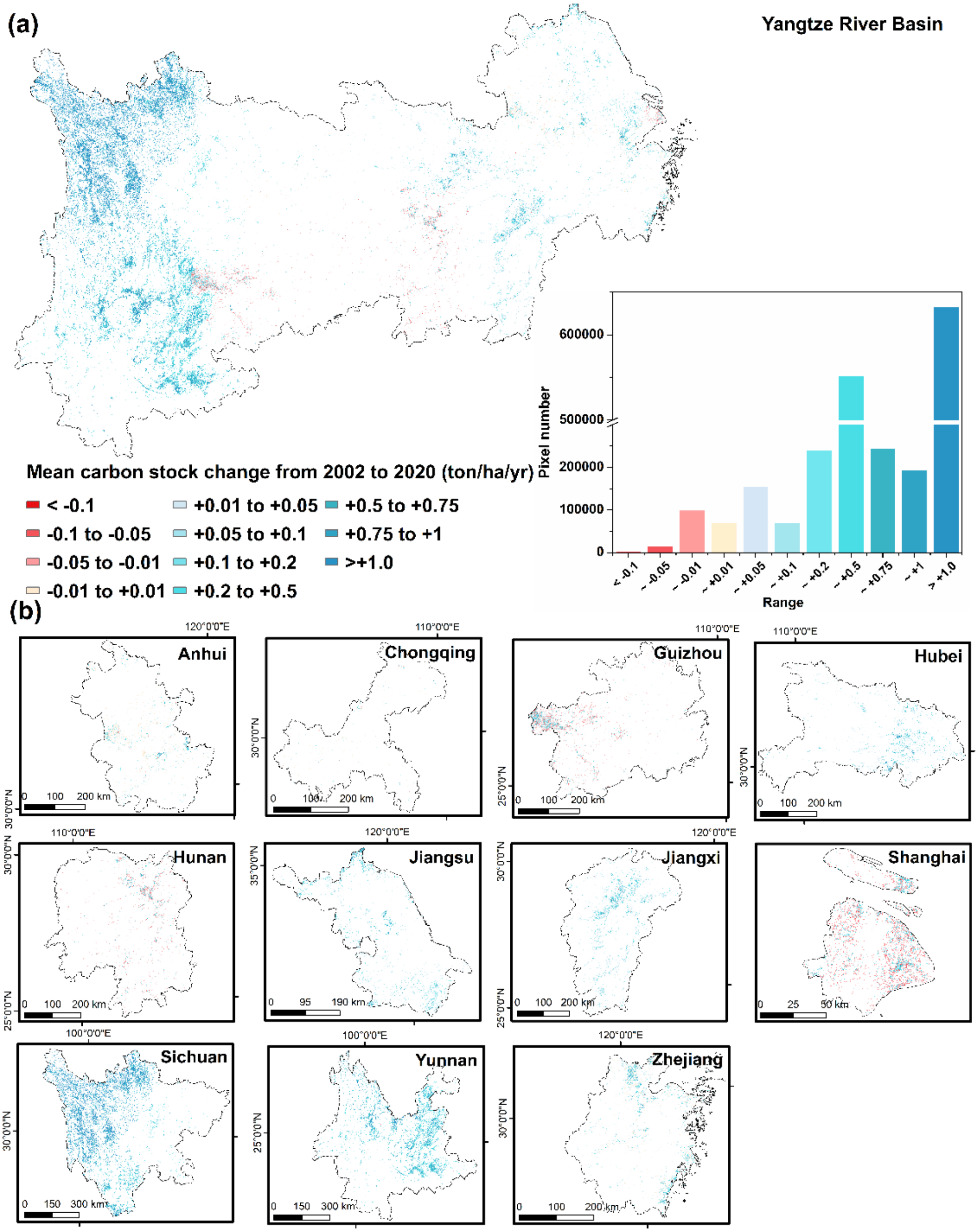

Figure 4-5. Carbon stock change in abandoned croplands and recultivation lands from 2002 to 2020, in terms of ton/ha/yr (250m resolution). (a) Overall carbon stock change extent across the entire region and histogram, and (b) in each province. The change value includes both mean carbon stock change in aboveground biomass, belowground biomass, and soil organic carbon over time. Aboveground biomass and belowground biomass were delineated using value from (Cook-Patton et al., 2020), soil organic carbon was from (Sanderman et al., 2023). The change value is calculated using the mean of the carbon stock change considering the entire studied period.

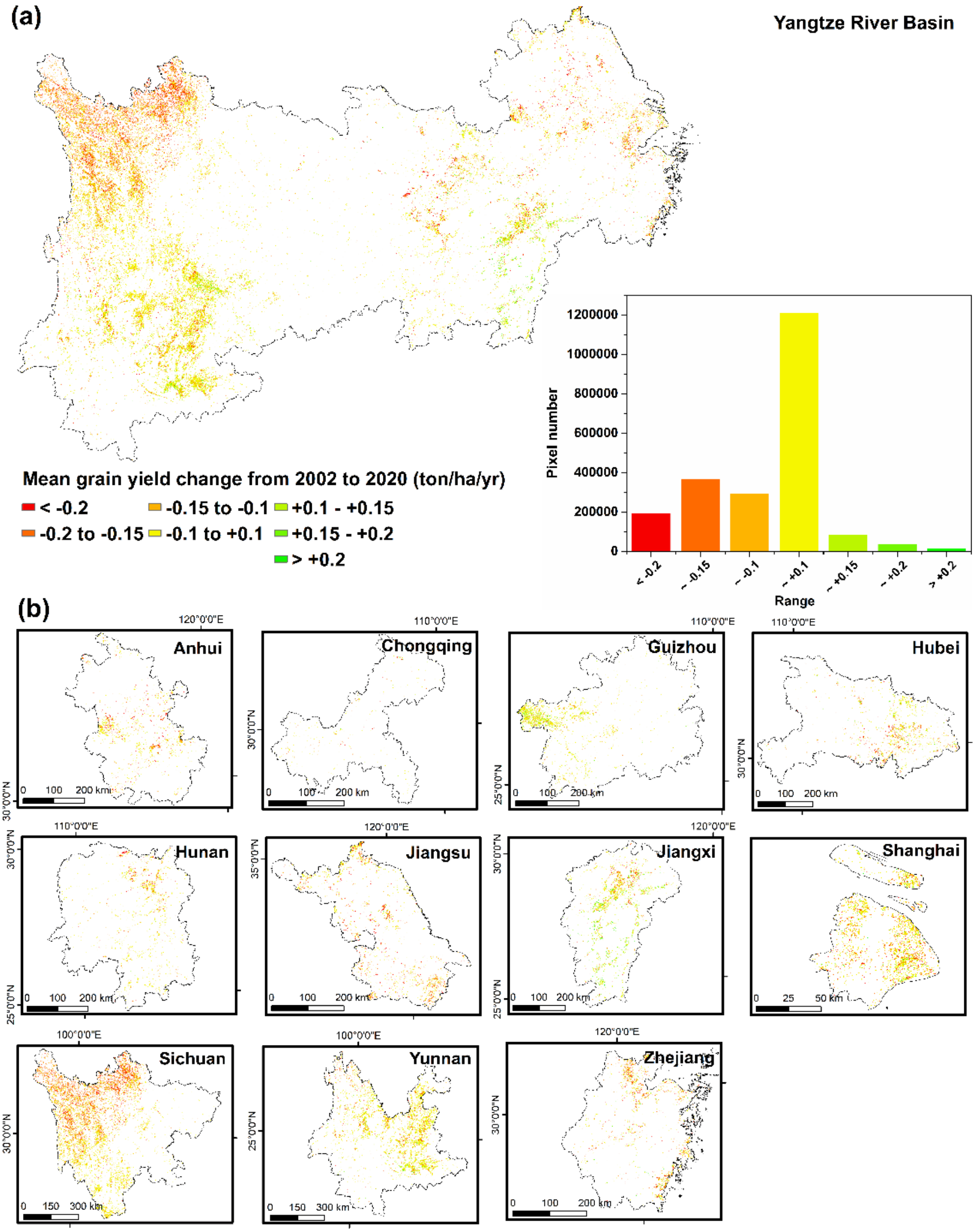

Figure 4-6. Grain yield change in abandoned croplands and recultivation lands from 2002 to 2020, in ton/ha/yr (250m resolution). (a) Overall grain yield change extent across the entire region and histogram, and (b) per province. The change value is calculated using the mean of the change in grain yield considering the entire studied period.

Table 4-1. Mean carbon stock change and grain yield change at each province as of 2020. "±" represents standard deviations (SD).

Province	Mean carbon stock change (ton/ha/yr)(SD)	Mean grain yield change (ton/ha/yr)(SD)
Anhui	0.14 (±0.27)	-0.06(±0.12)
Chongqing	0.10 (±0.21)	-0.05 (±0.12)
Guizhou	0.08 (±0.22)	0.01 (±0.10)
Hubei	0.20 (±0.32)	-0.05 (±0.12)
Hunan	0.09 (±0.25)	-0.05 (±0.11)
Jiangsu	0.27 (±0.35)	-0.08 (±0.13)
Jiangxi	0.17 (±0.26)	0.02 (±0.14)
Shanghai	0.04 (±0.14)	-0.05 (±0.11)
Sichuan	1.13 (±0.65)	-0.09 (±0.10)
Yunnan	0.50 (±0.40)	-0.02 (±0.10)
Zhejiang	0.18 (±0.28)	-0.08 (±0.13)

3.4. *Tradeoffs and synergies maps of carbon stock change and grain yield change*

The results highlighted varying trade-off and synergy relationships across provinces and over time(Figure 4-7). For instance, Anhui consistently demonstrated a trade-off, as indicated by correlation coefficients ranging from -0.89 to -0.8, although a positive trend (slope > 0, $p < 0.05$) suggested a slight weakening of this trade-off over time. Conversely, Hunan exhibited a fluctuating relationship, with correlations ranging from synergy (0.316) to trade-off (−0.457), and a negative slope of −0.029 ($p < 0.05$) indicating a strengthening of the trade-off in recent years. Similarly, Shanghai's relationship dynamically shifted between synergy and trade-off, with a negative slope of −0.023 ($p < 0.05$) indicating a gradual shift towards a trade-off.

In a more granular analysis at a 10 × 10km grid level from 2000 to 2020, our study revealed an array of trade-offs and synergies between carbon stock changes and grain yield variations in the Yangtze River Basin (Figure 4-8). A substantial 95% of the grids displayed trade-offs (Figure 4-8(b)), with strong correlation coefficients (-1 to -0.6) prevalent in 46% of all grids, notably in regions such as Yunnan-Guizhou, Jiangxi, and Hubei (Figure 4-8(c)). Moderate trade-offs were common in western Sichuan and other areas. On the other hand, 5% of the grids indicated synergies, predominantly found in Hunan and Shanghai. technologies and application for dynamic monitoring soil and water loss in the yangtze river basin, china

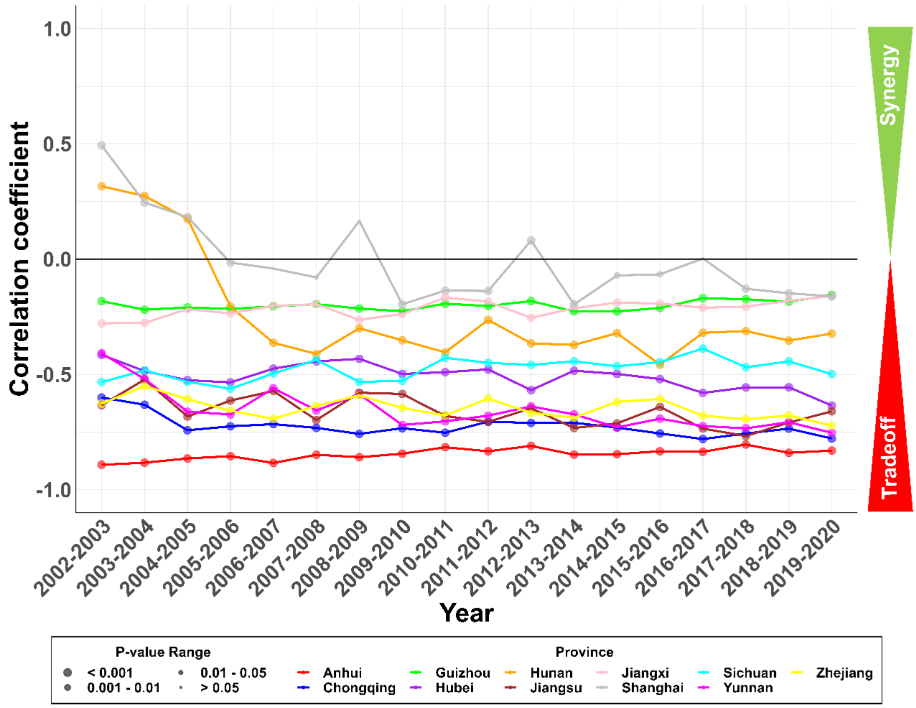

Figure 4-7. Temporal analysis of correlation coefficient of province. The transparent dot of different colors represents the different provinces and the size of the dot represents the range of p-value. when the correlation coefficient is less than 0, it represents that the annual changes in carbon stocks and grain production show a trade-off relationship, or it represents a synergy relationship. The color-coded labels on the right provide insights into the direction and statistical significance of the trend for correlation coefficient for each province over time.

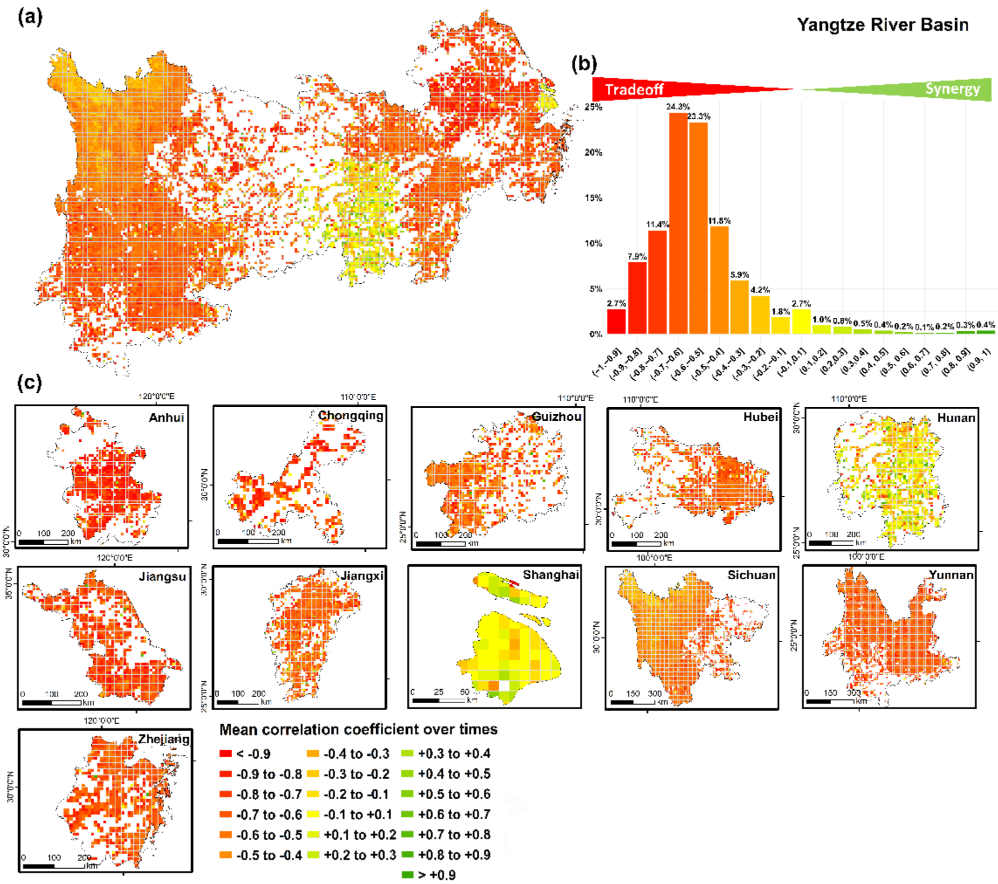

Figure 4-8. Mean correlation coefficient from over time. (a) overall correlation coefficient extent in the grid, (b) number of grid distribution, (c) provinces extent from (a). The mean value is calculated from the total of the correlation coefficients over times. When the grid value for a given year is null, it is not involved in the calculation. The spatial pattern of annual correlation coefficients in each province is placed in the supplementary (Figure S9-19). (b) Histogram of number of grids with correlation coefficients. We categorize the correlation coefficients, where -1 to -0.6 is strong trade-off, -0.6 to -0.2 is moderate trade-off, -0.2 to 0.2 is weak trade-off or weak synergy, 0.2 to 0.6 is moderate synergy, and 0.6 to 1 is strong synergy. The numbers above the bar chart represent the proportion of the grid in correlation coefficient interval to the total grid.

4. Discussion

4.1. Comparison with others studies

The extent to which cropland abandonment and recultivation provide opportunities for carbon sequestration and food production depends strongly on the extent and duration of abandonment. Using the new annual land cover time series, we found that the extent of cropland abandonment is high in different provinces of the Yangtze River Basin (Figure 4-3). However, by tracking land abandonment year by year, we find that most of the cropland abandonment is temporary (Figure 4-4), and its duration is much shorter than the whole time series (i.e. 19 years). Our study further underscores the evolving nature of these processes over time. Taking Sichuan as a case study, it stands as one of the regions with the longest average abandonment durations, however, short-term abandoned areas predominate over the long-term ones. Our simulations of scenario abandonment duration reveal that without recultivation, the average abandonment time in each province could be significantly longer, and abandonment is rarely observed in the final stages of our time series (Figure S2). This observation has profound implications for climate benefits and food production, demonstrating that abandonment and recultivation are not static phenomena but dynamic processes with significant environmental and agricultural impacts.

Our recultivation rate is generally consistent with the few existing comparable case studies in the literature that have examined this issue. However to the best of our knowledge, very few studies in the area covered by our study have used annual time series to examine cropland abandonment and recultivation. For example, Hou et al. (2021) this study examined agricultural abandonment in the Lower Yangtze River urban agglomeration from 2001 to 2018 and found that about 11.6% of agricultural land was abandoned, of which about 92% of the abandoned land was subsequently recultivated. This recultivation rate is similar to our result in Guizhou (87%), but higher than the average recultivation rate in our provinces (73%), and even higher than our estimation in Jiangsu and Zhejiang (63% and 62%, respectively). Another study suggests a national recultivation rate of about 30% for 1997-2019, with recultivation rate in Zhejiang at about 41% (Zhang et al., 2023a). Globally, Dara et al. (2018) examined a steppe region in northern Kazakhstan in 1991-2017 and observed that about 40.5% of the cropland was abandoned, of which about 20.0% of the abandoned cropland was recultivated, which is much lower than our results. This discrepancy may be due to (i) inconsistent definitions of abandonment and recultivation in different studies, where our definition would consider more reclutivation land; and (ii) inconsistent resolution of remote sensing data used in different studies, For example in the present study a resolution of 250m has been used, which is different from the resolution of 30 meter in some other studies.

In our study, we calculated that the average carbon stocks change rate across the different provinces varied between 0.08 and 1.1 tons/ha/year. This range is noteworthy when compared to the results of other studies in different geographical settings. For example, a study conducted in a karst region in southwest China reported an average carbon accumulation rate of 1.38 tons/ha/year during the recovery period following abandonment of agricultural land (Yang et al., 2016). This rate is higher than our calculated value, which may be largely attributed to differences in soil type and the nature of native vegetation across the study areas. However, data on carbon accumulation on abandoned cropland in Siberia showed an average rate of 0.66 tons/ha/year (Wertebach et al., 2017), which is a value that is more in line with our findings.

The discrepancy between results of various may be attributed to the method used for calculating carbon sequestration data. In our study, we extracted pixels representing the transition from cropland to natural vegetation and calculated the mean carbon change due to non-cultivation for at least two successive years, following the IPCC tier report method (IPCC, 2003, 2019). This approach is supported by other literature (Crawford et al., 2022). but assumes of a linear carbon accumulation post abandonment towards a new natural vegetation equilibrium considering a transition period of 20 years. To estimate the annual carbon accumulation, we used recent literature data (i.e. 2.38 tons/ha/yr) which was validated in China by Cook-Patton et al. (2020) and SOC change measured by Sanderman et al. (2023), combining this with the abandonment duration to calculate potential carbon accumulation during abandonment. It should be noted that this linear C accumulation is a simplification as some studies have shown also the existance of non-linear C reponses following land use change (Poeplau et al., 2011). Hence, in future research this aspect of the work could be improved by adopting these non-linear response curves.

The ratio of cumulative grain production loss to the cumulative area of abandoned cropland across the Yangtze River Basin was calculated to be 3.1 tons/ha, which is a bit smaller that the 5.5 tons/ha in Jiang et al. (2023) and 3.4 tons/ha in Guo et al. (2023).. This variance can likely be attributed to the distribution of abandoned croplands in mountainous regions within our study area, where the yield per hectare is generally lower due to the terrain and other environmental factors. In summary, these comparisons highlight the variability in carbon sequestration rates and agricultural productivity losses in abandoned croplands across different regions. Such variability underscores the importance of considering regional characteristics when evaluating the ecological and economic impacts of land abandonment.

4.2. Implication for climate change mitigation and food security

Our research shows that in a world where land scarcity remains a major constraint to sustainable development, abandoned cropland can be a promising way to release additional land resources. If strategically recultivation and/or left abandoned, abandoned cropland can make a significant contribution to achieving food security and climate change mitigation goals. In addition, reforestation through the long-term regeneration of abandoned cropland can provide a range of co-benefits such as improved biodiversity conservation, water filtration, air filtration and soil quality (Feng et al., 2005; Fischer et al., 2012; Khanal and Watanabe, 2006). The cumulative abandoned cropland of 21490 × 10^3 ha also shows great potential for ecological restoration, e.g. by 2020, abandoned cropland in the Yangtze River Basin could accumulate more than 379 Mton C (excluding recultivation), and could mitigate carbon emissions (Luo et al., 2020).

However, the negative impacts of abandonment on agricultural production are undeniable. Our study further reveals that during the interactive processes of abandonment and recultivation, cumulative grain production decreased by approximately 13.47 Mtons over time. This equates to a cumulative energy loss of 29.9 Pcal (1 Peta-calories = 10^{12} kcal) when converted from actual weight production to calorie-based dry weight production (Table S14). According to the latest "China Food and Nutrition Development Outline" (https://www.gov.cn/govweb/zwgk/2014-02/10/content_2581766.htm), with a daily per capita energy requirement of 2200-2300 kcal, the energy loss could sustain an additional 35.6 to 37.2 million individuals as of 2020.

It is important to note that social factors may hinder efforts to utilise abandoned land. For example, interprovincial migration of populations reduces carbon emissions during agricultural production, but heavy reliance on fossil fuels may offset these benefits, leading to an increase in overall ecosystem carbon emissions (Bu et al., 2022; Chen and Yang, 2018; Shi and Chang, 2023). In addition, a continued shift towards meat-intensive diets may limit the potential of abandoned agricultural land for food production (Tilman and Clark, 2014). This is because livestock-based production requires more land than grain-based production to produce the same number of calories (Shukla et al., 2019). In our study, we assumed that all selected crops were consumed directly by humans and not as animal feed. However, a recent study predicts that more than 34 % of crop production in China and globally will be used to feed livestock (Long et al., 2018; Tang et al., 2015; Zhao et al., 2021a). These social dynamics highligh the multifaceted challenges in sustainably managing abandoned cropland. The interplay between human behavior, dietary preferences, and energy consumption patterns poses additional layers of complexity to the already intricate balance of carbon sequestration and food production across the Yangtze River Basin.

4.3. Competition between carbon sequestration and food production

In the Yangtze River Basin, the subtle interactions between changes in carbon stocks and changes in grain production across provinces reveal intriguing temporal dynamics (Figure 4.7). A clear and stable trade-off relationship emerged in almost all provinces. Studies have shown that carbon stocks increase slowly in the first few years after abandonment of ploughing, before increasing significantly after a decade (Schierhorn et al., 2013). In our study area, carbon stocks likewise rose slowly, largely because few arable lands were abandoned for more than a decade. Reductions in grain yield due to abandonment are instantaneous and are usually no longer included in calculations in the year of abandonment. At the same time, the recovery in grain yield from recultivation is also an instantaneous benefit, and the true impact on regional grain yields is smaller than expected. To stabilize or even reduce the trade-off between ecosystem services, the role of recultivation needs to be further examined.

We calculated cumulative carbon storage changes and cumulative grain production changes considering the ‘real abandonment’ (with recultivation) and ‘scenario abandonment’ (without recultivation), respectively (Figure S4). There is no doubt that recultivation of abandoned land hinders carbon accumulation in the study area and slows down the decline in food production. However, without recultivation, the degree of trade-off between climate change mitigation and food security would have been stronger. Therefore, rational recultivation is more conducive to reducing the trade-offs between ecosystem services and becomes a key lever for balancing ecosystem services. Recognising these findings, there is clear potential for strategic land use planning to transform existing trade-offs into synergies.

Grid-scale trade-off analyses demonstrating the temporal volatility of correlation coefficients similarly demonstrate that, in specific regions, recultivation can contribute to the reduction of trade-offs and even convert them into synergies. For example, agroforestry resulting from recultivation near secondary forests on abandoned croplands in the Yangtze River Basin. Combining tree growth with sustainable land use leads to synergies between carbon sequestration and food production (Guo et al., 2020), highlighting the environmental protection capacity and agricultural productivity (Távora et al., 2022). Another notable example of translating trade-offs into synergies is the recent implementation of the High Standard Cropland (HSCP) strategy in the Yangtze River Basin region. By analyzing provincial-level panel data in China, high-standard farmland not only achieves increased food production (Hao et al., 2024), but also carbon emission reductions of 3.9-10.1% (Li et al., 2023; Xiong et al., 2023; Yang et al., 2022). This suggests that the potential for carbon sequestration can be achieved by appropriate recultivation while maintaining or even increasing food production.

5. Conclusion

Changes in agricultural land use have significantly shaped the landscape across the Yangtze River Basin. Despite widespread cropland abandonment, the agro-ecosystem continues to impact key ecosystem services change like carbon stock change and grain yield change. Our analysis proposes a unique approach to uncover the relationship between sustainable indicators and their spatio-temporal pattern at the multi-level in the context of widespread cropland abandonment and recultivation.

Our findings show widespread cropland abandonment across the Yangtze River Basin, totaling 21490×10^3 ha. However, nearly 74% of this land underwent recultivation. We observed interannual and regional differences in these trends. In this study, we employed InVEST and NDVI-Statistical integrated analyses to assess changes in carbon stock and grain yield across the Yangtze River Basin from 2002 to 2020. We observed significant spatio-temporal variations in these ecosystem service changes. Our analysis highlights significant potential for carbon stock increase, ranging from 0.1 to 1.1 tons/ha/yr across provinces during natural regrowth in the Yangtze River Basin. However, by 2020, the observed carbon accumulation was only 48.1% of its potential, mainly due to recultivation. Regarding food security, land abandonment generally led to decreased grain production, except in Guizhou and Jiangxi where increased recultivation offset the decline. Overall, abandonment resulted in a reduction of grain production by 13.47 Mtons, equating to an additional caloric need for 35.6 to 37.2 million people. We employed the Spearman correlation method to evaluate trade-offs and synergies in multi-level ecosystem service changes. Our analysis reveals multifaceted interactions between changes in carbon stock and grain yield in the Yangtze River Basin from 2002 to 2020. A predominant negative correlation highlights prevalent trade-offs in provinces like Anhui, whereas regions like Hunan and Shanghai exhibited fluctuations between synergy and trade-off.

Spatially, 95% of observed grids showed clear trade-off, most pronounced in the western and eastern regions, while 5% indicated synergistic conditions, primarily in Hunan and Shanghai.

The Yangtze River Basin faces a complex trade-off between climate change mitigation and food security. While replanting undermines some of the progress made in climate change mitigation, it significantly contributes to food security, thereby reducing the severity of this trade-off. Despite the effectiveness of current replanting methods , food production increases remain limited. Going forward, it is imperative that more scientifically based replanting programmes be adopted. Such an approach could transform trade-offs into synergies that could contribute to the achievement of the global climate goals set out in the Paris Agreement and align with Sustainable Development Goals 2 (Zero Hunger) and 15 (Life on Land). This strategic shift is essential to simultaneously address the twin challenges of climate change and food security and to promote ecological restoration.

6. Supplementary information

All supplementary information mentioned in this Chapter is included at the end of the thesis Appendix.

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Chapter 5

Synthesis of findings

1. Integration of results

The main objective of this thesis is to provide a comprehensive understanding of cropland dynamics across main production area in China (Figure 5-1). Chapter 2 addresses the challenges and strategies for increasing grain production in China in order to meet the growing demand for food at the beginning of the 21st century, at a time when the cropland was limited. Using the decomposition method, and GlobeLand30 land cover data, this chapter evaluates how cropland intensification (yield and MCI) and large-scale utilization (MPS and NP) affect grain production at national and county levels. This analysis emphasizes the vital role that sustainable agricultural practices and land use management play in achieving food security objectives.

Having discussed the contributions of cropland intensification and large-scale utilization to national grain production increases, Chapter 3 shifts focus to specific challenges that threaten the sustainability of these cropland. This includes cropland abandonment and recultivation, highlighting the critical need to understand and manage land use changes. Such management is crucial for achieving the Sustainable Development Goals (SDGs) in main grain-producing regions like the Yangtze River Basin. Chapter 3 delves into the spatiotemporal dynamics of cropland abandonment and recultivation across the Yangtze River Basin from 2000 to 2020, employing remote sensing techniques. This chapter introduces a novel methodological framework that highlights the complex interactions between cropland abandonment and recultivation within a clearly defined spatiotemporal context across extensive geographic areas.

Building on the understanding of land use dynamics, Chapter 4 explores the implications of cropland abandonment and recultivation on climate change mitigation and food security. This analysis reveals a significant trade-off between enhancing carbon stocks and maintaining grain production. The primary focus of this chapter is to map and analyze the impacts of these land use changes on climate change mitigation and food security, examining the resultant trade-offs. The study identifies spatial variations in these trade-offs, highlighting how strategic land management and restoration programs can balance environmental goals with food production objectives.

This chapter collectively weaves together the results obtained from each chapter, highlighting the logical progression of the study's focus areas. It underscores the interconnectedness of agricultural practices, land use changes, and broader environmental and food security goals, especially with a particular focus on the Yangtze River Basin the Yangtze River Basin. Moreover, it stresses the importance of adopting holistic and nuanced policies and management strategies that simultaneously address increasing crop production, ensuring food security, and contributing to climate change mitigation. This comprehensive analysis provides valuable insights, offering a framework for policymakers and landscape managers to navigate the complexities of sustainable land use with the aim to improve environmental and socio-economical conditions. The forthcoming paragraphs will elaborate on how the thesis addressed specific objectives and research questions (RQs) outlined in the introduction (Chapter 1).

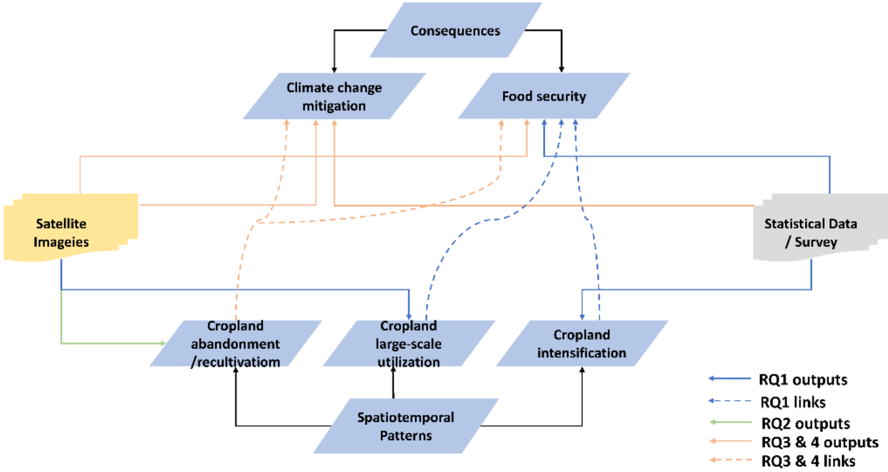


Figure 5-1. Schematic diagram of the integration of various results obtained in the present thesis. The solid lines indicate the outputs corresponding to each research question (RQ), while the dotted lines indicate the links corresponding to each research question.

1.1. Driving factors to the grain production increase: cropland intensification and large-scale utilization (RQ1)

This comprehensive study assessed the impact of cropland intensification and large-scale utilization on China's grain production between 2000 and 2010, revealing a significant positive trend in national crop production. The increase is attributed primarily to enhancements in yield and the Multiple Cropping Index (MCI), along with adjustments in the Number of Parcels (NP) and Mean Parcel Size (MPS). Despite the negative impacts of decreased MPS indicating cropland fragmentation issues, the substantial contributions from improved yield (+77%) and MCI (+27%) were noteworthy. The results emphasize the crucial role of cropland intensification in increasing grain production, while large-scale utilization may offer significant potential for future increased production. Therefore, the first priority is to maintain sufficient cropland area across China, especially in the main grain-production areas.

1.2. Spatiotemporal of dynamics of cropland abandonment and recultivation: extent, area and interaction (RQ2)

This study explored the spatial and temporal dynamics of cropland abandonment and recultivation in the Yangtze River Basin, uncovering significant land use changes from 2000 to 2020. The study highlights the prevalence of abandonment in areas with slopes less than 5°, notably in high-altitude regions of Sichuan, Yunnan, Jiangxi, and Zhejiang, where over 70% of abandoned land was quickly recultivated. Furthermore, we discovered that over 50% of the abandoned land was recultivated within three years. Utilizing MODIS time series data, this study introduces a novel approach to analyze the complex interactions between these processes, offering a methodological framework for assessing large-scale agricultural land use dynamics.

1.3. Consequences and tradeoffs on ecosystem services after cropland abandonment and recultivation: climate change mitigation and food security (RQ3 & 4)

Changes in agricultural land use, particularly cropland abandonment and recultivation, have significantly altered the landscape of the Yangtze River Basin, impacting ecosystem services such as carbon stock and grain yield. Our study reveals extensive cropland abandonment (approximately $21{,}490\times10^3$ ha), with about 74% subsequently recultivated, showing regional and annual variations (Chapter 3 and RQ2). By employing InVEST and NDVI-Statistical analyses from 2002 to 2020, we identified significant spatio-temporal differences in carbon stock and grain yield changes. Despite the potential for increased carbon storage, ranging from 0.08 to 1.1 tons/ha/yr, actual carbon accumulation by 2020 reached only 48.1% of this potential, which could be largely explained by recultivation practices. Overall, grain production declined, except in regions where recultivation compensated for these losses, resulting in a net reduction equivalent to the caloric needs of between 35.6 to 37.2 million people. Spearman correlation analysis revealed complex interactions between carbon stock and grain yield changes, with a general trade-off observed in most areas, although some regions displayed potential synergies.

2. Policy implications

To ensure future food supply while adhering to sustainable land management and enhancing crop production, a comprehensive approach is essential. This approach should not only bridge the gap between current agricultural practices and advanced sustainability concepts but also address key issues like cropland abandonment and the improvement of recultivation techniques. These measures are crucial for strengthening food security, preserving ecological integrity, and achieving environmental benefits, thereby laying the groundwork for sustainable agricultural progress.

In response to these challenges, the proposed policy framework emphasizes genetic innovation and the adoption of advanced agricultural practices as key elements. Given the slowing growth rates in crop yields across major grain-producing areas, an urgent shift in strategies is necessary (Ray et al., 2013). Focusing on genetic enhancement and implementing Multiple Cropping Index (MCI) strategies in regions facing biophysical challenges, like the mountainous southwest of China, offers an vital opportunity to overcome limitations in grain production improvements (Huang and Ding, 2016; Yan et al., 2019; Zuo et al., 2014). To catalyze these advancements, support mechanisms such as financial incentives for advanced irrigation, land consolidation, and service centers for land transfer and mechanization are recommended, thereby contributing to "Ensuring Sustainable Consumption and Production (SDG12)" (Cao et al., 2020a; Evenson and Gollin, 2003; Huang and Ding, 2016; Li and Shen, 2021; Pingali, 2012).

Both "Requisition–Compensation Balance Project" and " High Standard Farmland Project" can effectively increase land productivity by ensuring a stable total land use balance, preventing cropland fragmentation and fertile land abandonment (Hao et al., 2024; Pu et al., 2019; Song and Pijanowski, 2014; Xin and Li, 2018; Yu et al., 2020). The implementation of these land use projects has promoted land consolidation and encouraged the reclamation of abandoned land suitable for cultivation, thereby increasing the area of cultivated land and ensuring food production. In addition, the negative impacts of land fragmentation are reduced, making modern agricultural practices and mechanization easier to implement. The consolidated plots facilitate the use of advanced agricultural equipment, improve irrigation efficiency, and improve overall farm management. This not only prevents the abandonment of fertile land, but also encourages the sustainable use of marginal land through improved farming techniques and soil management practices, thereby helping to increase crop yields and resource utilization.

To enhance the recultivation of abandoned croplands, additional agricultural strategies are crucial. Investment in agricultural research and development can lead to breakthroughs in crop breeding and sustainable farming practices, specifically tailored to recultivted lands and reduce the cost of recultivated (Pazúr et al., 2020). Precision agriculture technologies, such as GIS and data analytics, can optimize resource use and increase yields on recultived croplands (Grella et al., 2023). The promotion of sustainable farming practices, such as conservation tillage and crop rotation, can markedly enhance soil health and biodiversity on recultivated croplands (Liu et al., 2021).

Building on the foundation of innovative agricultural practices, achieving a balance between agricultural productivity and ecological integrity is a foundational goal of these policy recommendations. A precise evaluation of abandoned croplands is essential for understanding their ecological and environmental effects, particularly in mountainous regions where abandonment is common. Utilizing time-series data for accurate estimations of these lands is crucial, as inaccuracies could significantly overestimate the total soil organic carbon sequestration potential (Crawford et al., 2022). Interestingly, the majority of abandoned land is typically recultivated within three years, indicating a pattern of intense cropland utilization and suggesting that increasing food production through cropland area expansion can significantly alleviate food shortages. However, prioritizing ecological benefits remains paramount, as overlooking the transient nature of agricultural abandonment risks sacrificing significant ecological gains, such as biodiversity and carbon sequestration (Corbelle-Rico et al., 2022).

Moreover, large-scale cropland recultivation projects intended to benefit local livelihoods may fail due to inefficient new cropland use (Deng et al., 2021; Xin and Li, 2018), especially when local socio-economic contexts are ignored (Coleman et al., 2021). Therefore, involving local communities in policy-making is crucial to balance biodiversity, carbon storage, and livelihoods, highlighting a complex nexus that requires further research. This recognition of the multifaceted challenges informs our next steps: (i) Optimizing recultivation practices necessitates thorough soil nutrient management and (ii) the formulation of comprehensive policies to guarantee the sustainability and effectiveness of these efforts.

Despite improved yields on recultivated lands compared to pre-abandonment levels, they still fall below regional and national averages, as illustrated in Figure 5-2. This highlight the need for policies that both ensure recultivation sustainability and enhance the accessibility, affordability, and efficiency of food production. Furthermore, considering alternative uses for recultivated croplands, like bioenergy crop cultivation, presents a strategy to meet climate goals and food security challenges, emphasizing the recommendations' multifaceted nature.

These strategic policy considerations lead us to a broader perspective on the sustainability of food systems. Besides ensuring the durability of recultivation for increasing food supply, enhancing the accessibility, affordability, and efficiency of food production is essential (Webb et al., 2006). It's vital to ensure reliable local food resources to support the livelihoods of local farmers (Wang et al., 2019), as well as improving food yields and Multiple Cropping Index to avoid area-based grain production increases on a single area (Long et al., 2022). Incorporating additional information, including cropland suitability for development and demographic data, can inform actions for rational recultivation (Schneider et al., 2022).

As we consider the wider implications of these strategies, the climate change mitigation potential of abandoned cropland can be converted into actual carbon reduction targets (UNFCCC, 2021), achieving carbon offsets via trusted carbon markets, thereby enhancing food trade market circulation to offset food losses. This comprehensive view guides our approach to recultivation, not just as a means to restore productivity but as part of an integrated strategy for sustainable land use.

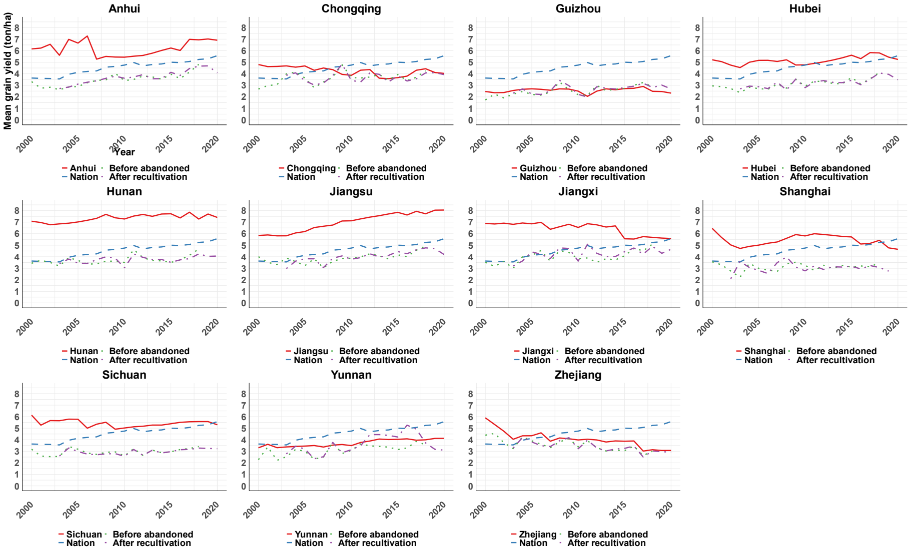


Figure 5-2. Trends in mean grain yield of before abandoned and after recultivation compared to grain yield at provincial and national levels in the period of 2000-2020. The period for "Before abandoned" cropland is calculated for 2000-2018 and the period for "After recultivation" cropland is calculated for 2003-2020. Before abandoned croplands represent abandoned cropland maintained in a cultivation before abandonment. The solid red line represents the mean yield in each province, the solid blue line represents the mean yield of China, and the dash green line and dash purple line represent the mean yield of pre-abandonment cropland and recultivation cropland in each province, respectively.

3. Limitations

This study presents limitations common to research on agricultural productivity, land use change, and ecosystem services assessment across diverse landscapes. Specifically, Chapter 2 faces the challenge that temporal scope is limited to only two time points, 2000 and 2010. This constraint might overlook short-term fluctuations in crop production, as changes may not manifest clearly in decadal analyses. The reliability of statistical data, especially regarding yield estimations, presents uncertainties due to potential overestimations or underreporting (Ash and Edmonds, 1998; Tan et al., 2017; Verburg and Chen, 2000). For instance, if collected crop production values are lower than actual one, our analysis might underestimate yield contributions and overestimate MCI contribution. In 2000 and 2010, we found that the correlation between the decomposition factors was very weak, hence, we can assume that the decomposition factors were independent of each other. However, this assumption may also affect the stability and interpretability of the model.

Chapter 3 also navigates methodological challenges in distinguishing between cropland abandonment and recultivation, highlighting the complexity of accurately capturing land use dynamics. Using a uniform definition of cropland abandonment and recultivation across extensive areas presents several issues. First, large-scale studies, including ours, might not fully account for seasonal abandonment and fallow patterns, possibly leading to an underestimation of cropland abandonment as areas marked as cropland in annual data might include seasonally abandoned plots. Secondly, differentiating between "permanently abandoned cropland" and temporarily fallow land is challenging due to their similar spectral characteristics in initial stages. Lastly, applying the same threshold duration value across diverse farming systems may overlook abandonment in systems characterized by relatively short abandonment periods, potentially overestimating the extent of recultivation of abandoned cropland.

Moreover, MODIS satellite data was chosen as the primary source for mapping cropland abandonment at large scale due to its coverage of extensive areas and more frequent data observations. However, the usage of 250m resolution MODIS imagery could be challenging to map cropland in the southern region of China, as the fragmentation of land patches tends to bring significant “mixed pixels” (Vicenteserrano et al., 2008), potentially leading to an underestimation of cropland abandonment.

In Chapter 4, we assessed carbon stock across various landscapes using the carbon sequestration module of the InVEST model, encountering limitations due to reliance on provincial carbon pool data. Additionally, while we recognized and used meteorological factors to correct for carbon pool data, we did not consider the effects of variables such as soil type, pesticide residues and vegetation type (O'Bryan et al., 2022; Oechaiyaphum et al., 2020; Wang et al., 2021). Another uncertainty in Chapter 4 comes from possible errors in the statistics, as there may have been someinaccurate reporting of China's provincial grain production data (Liu et al., 2020b). In addition, the accuracy of NDVI imagies has an important impact on the robustness of models that rely on NDVI (Butt, 2018). While NDVI in mixed-use areas, like forests and croplands, can skew the data, leading to inflated production figures.

4. Future researches

To effectively address the complex challenges at the intersection of agricultural productivity, sustainable land management, and environmental conservation, developing a strategy that meticulously balances the quest for higher crop yields with the imperatives of sustainable land utilization is imperative. This balanced approach is vital for advancing our comprehension and management of critical environmental functions such as carbon sequestration. A nuanced approach that refines agricultural data collection methods, improves environmental assessment methodologies, and conducts a broader analysis of ecosystem services impacted by land use changes. Each of these facets is fundamental to policy-making process defining agricultural practices that are not only environmentally sound but also socio-economically sustainable.

A pivotal area for future investigation involves enhancing and integrating agricultural data, particularly concerning crop types. Currently, the availability of crop-specific data is limited; for instance, the Multiple Cropping Index (MCI) is often provided at the county level as an average value for all crop types, due to the scarcity of detailed crop-type information. This limitation hinders our ability to understand and quantify the impacts of crop diversification on production levels, a topic explored in Chapter 2. Employing GIS techniques alongside crop-specific datasets presents a promising approach for examining the spatial patterns of crop composition changes and their effects on agricultural productivity. For example, adopting a remote sensing based Spatial Allocation Model (You and Wood, 2006) could significantly enhance this analysis. Specifically, the direct calculation of cereal yields using remotely sensed data offers a promising alternative to traditional statistics. This approach avoids the inaccuracies associated with the manipulation of historical data. Therefore, prioritizing the reinforcement and amalgamation of agricultural data, especially regarding crop types, is identified as a critical area for future research endeavors.

The accurate monitoring of cropland abandonment and the distinction between land that is temporarily fallow and abandoned cropland are crucial, highlighting the need for advanced remote sensing technology and higher-resolution datasets. Fallow land is characterized by a continuous cover of herbaceous vegetation, which tends to increase in density as the fallow period lengthens (Bratic et al., 2023; Wu et al., 2014b). These areas often exhibit clear signs of human activity aimed at managing the land and facilitating the rapid resumption of agricultural production. In contrast, abandoned land typically shows a trend towards natural vegetation growth, indicating less human intervention. Future research should therefore employ a combination of time-series multispectral remote sensing imagery and high-resolution images to analyze surface texture features. This approach will enable researchers to accurately differentiate these land uses, providing essential insights for effective land management strategies.

Additionally, our findings in Chapter 3 reveal that the shorter duration of abandonment across the Yangtze River Basin indicates a dynamic of cropland abandonment, which may be partly attributed to seasonal fallow. Seasonal abandonment occurs in areas where multiple cropping is practiced, and it typically happens when farmers reduce labor inputs and capital investments during certain seasons. This observation underscores the necessity for future research to develop improved methodologies for capturing the spatial and temporal dynamics of both long-term and seasonal cropland abandonment across extensive study areas.

Future research in ecosystem services estimation should prioritize integrating biophysical models and enhancing geographical datasets to overcome current limitations in assessing carbon stocks and grain production. The carbon response to land use change is neither linear nor symmetric. Poeplau et al. (2011) demonstrated that soil organic carbon (SOC) increases slowly and takes decades to stabilize during the transition from cropland to natural vegetation. Conversely, in the transition from grassland to cropland, SOC depletes rapidly, often within a few years. To improve this, advanced models that better reflect these non-linear and asymmetric dynamics will be used. These models will incorporate empirical data to provide more accurate representations of SOC changes, enhancing the reliability and precision of carbon stock estimations and contributing to more effective land management and climate mitigation strategies. Furthermore, the long-term effects of climate change on soil organic carbon pools must be considered, given the significant impact that climate change is likely to have on these carbon pools considering remarkably longer time period (e.g. a century) (Meersmans et al., 2016).

Alternatively, by incorporating process-based carbon models (e.g. Century, RothC, DNDC) instead of the carbon sequestration module of the INVEST model, future studies can more accurately represent biophysical processes involved in changes in carbon stocks. This approach will benefit from refining the base map to include detailed data on soil and vegetation types, significantly improving the accuracy of carbon assessments. More importantly,

Field data validation is essential to ensure model accuracy and reliability. Specific aspects that could be validated include in the near future: 1) Carbon sequestration. Conduct soil sampling at various depths and locations within different land use types. Analyze the samples for SOC content using standard laboratory methods such as dry combustion. Compare these field measurements with model predictions to validate carbon sequestration estimates; 2) Grain yield. Collect grain yield data directly from fields across different provinces. Use crop cutting experiments or harvest records from farmers to obtain accurate yield data.

Similarly, addressing the scarcity of spatial datasets for grain production is crucial, especially considering the challenges of data misreporting from lower administrative levels in China and the pronounced heterogeneity in hilly regions. Enhancing methodologies related to the Normalized Difference Vegetation Index (NDVI) will help mitigate inaccuracies caused by its current limitations, such as misinterpretations in mixed-use areas. This improvement is essential for more accurate assessments of vegetation health and food production potential.

Expanding research to fully appreciate the broader implications of ecosystem services is essential for understanding the interdependencies between agricultural practices, land use transformations, and environmental sustainability. Future studies should explore the array of ecosystem services that abandoned croplands provide, including spillover effects like habitat expansion. Such expansions can boost biodiversity and intensify human-wildlife interactions, which may in turn elevate the risk of zoonotic disease transmission. Gaining this insight is critical for formulating comprehensive land-use strategies that adeptly balance ecosystem benefits with disease risk management. Additionally, this research is key to unraveling the complex trade-offs and advantages of various land use strategies, and especially their effects on ecosystem sustainability and human well-being.

Additionally, it is crucial to quantify the relationships between ecological drivers and the sustainability of abandoned sites by exploring the trade-offs and synergies of ecosystem services across various scales. Research should evaluate the regional potential of abandoned land for enhancing human well-being through initiatives such as afforestation, food production, and ecological habitat creation, while meticulously considering spatial scale differences, including watershed, sub-watershed, administrative areas, and grid scales (Qiao et al., 2019). A thorough investigation is required to elucidate the impacts of land use modifications—whether through deliberate recultivation or transformation into ecological preservation areas—on a broad array of ecosystem services. Studies examining abandoned croplands for purposes like reforestation, food production, or habitat creation need to pay close attention to spatial scale nuances. This approach will yield crucial insights into how land use decisions synergistically affect climate goals and sustainable development (Næss et al., 2021; Zheng et al., 2023). Such a comprehensive method will provide valuable insights for ecological policy planning and implementation, focusing on spatial patterns and offering technical support for effectively managing abandoned lands.

In conclusion, enhancing the linkages among these pivotal research domains underscores the urgency for a holistic and integrated methodology to more adeptly comprehend and navigate the complex interplay between agricultural productivity, land management, and environmental stewardship. This comprehensive approach not only seeks to bridge current research deficits but also lays the groundwork for sustainable interventions that concurrently serve environmental and societal interests. Through focused endeavors on data enhancement, innovation in methodology, and an all-encompassing evaluation of ecosystem services, future research holds the potential to significantly steer the development of agricultural and environmental governance strategies towards a more sustainable horizon.

Appendix

Chapter 4 Supplementary information

Supplementary information 1: Spatial temporal character of other conversion, and abandonment duration

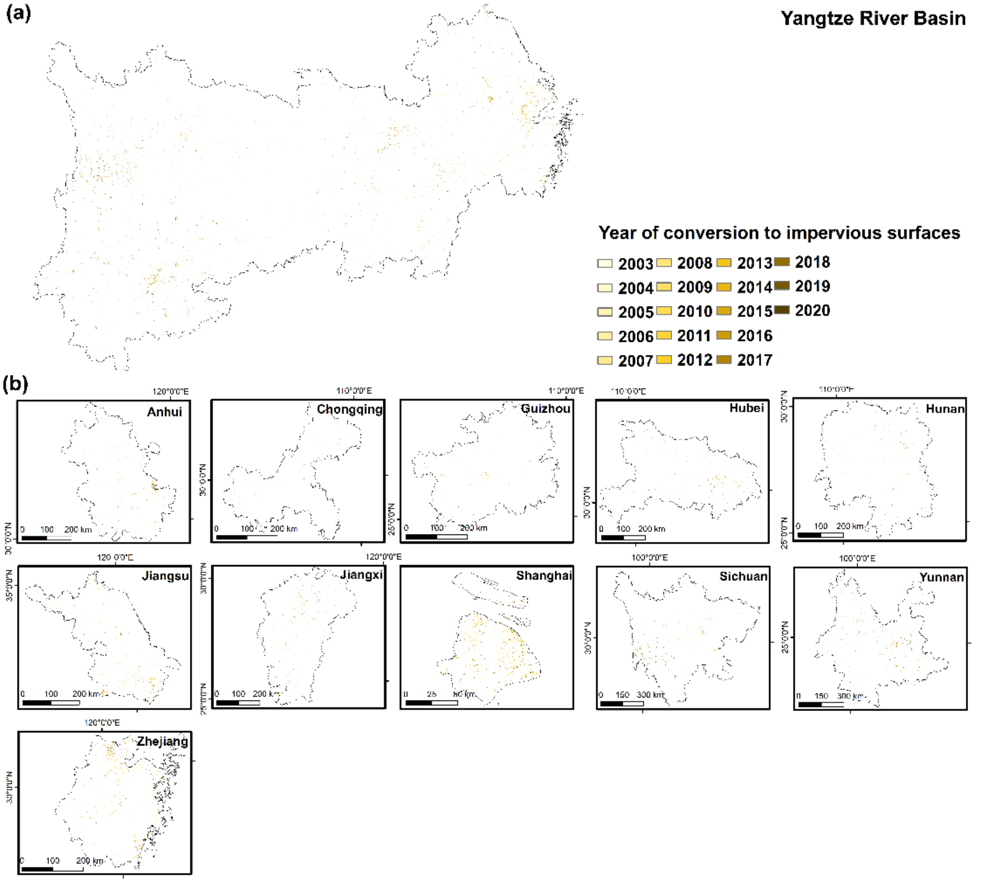


Figure S1. Spatio-temporal pattern of abandoned land converstion to impervious surfaces. (a) Overall conversion to impervious surfaces extent and (b) in each province.

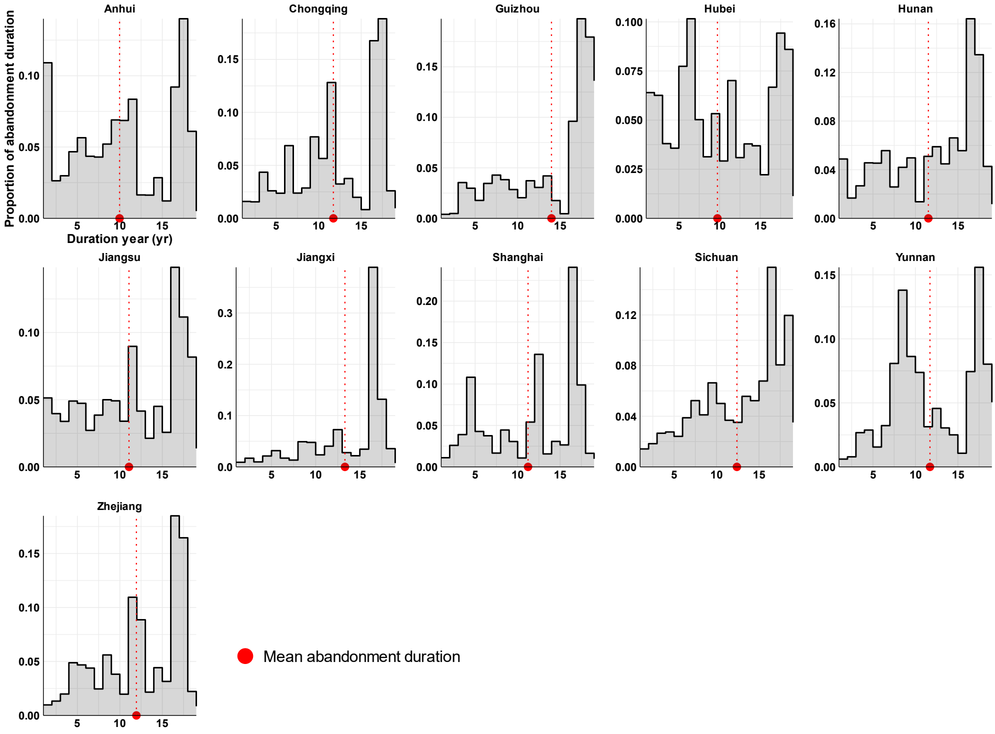


Figure S2. Distribution of scenario abandonment duration through time in each province. The distribution of abandonment duration (in years) for all periods of abandonment from 2002 to 2020. The y axes show the proportion of abandonment area of a given durationin in each province. The red points and vertical dashed line represent the mean abandonment duration (in years) at each province. Note that these distributions exclude multiple periods of abandonment for those pixels that experienced abandoned lands loss during the time series.

Supplementary information 2: Carbon Sequestration module parameterization for InVEST

Supplementary information 2.1 Data requirement

Table S1. Data requirement for the Carbon Sequestration module.

Data	Type	Data source	Note
Land use/ cover	Raste r	Land classification data	LULC of the year over 2000-2020, including cropland, grassland, forest, shrubs, bareland, impervious surface, wetland, and water. Resolution is 250 ×250 m
Carbon pool	.CSV file	Intergovernmental Panel on Climate	Carbon pool attributions of each LULC

		Change (IPCC) and other literatures	
Climate parameter	Shapefile, Raster	http://data.cma.cn/en, covering 101 national stations	Interpolation of site data to obtain raster data

Supplementary information 2.2 Carbon pool data calibration

Biomass and soil organic carbon pool data are both significantly positively correlated with precipitation, while the correlation with annual average temperature is weak. We calibrated biomass and soil organic carbon pool data with climate parameters (Table S2) as follows:

$$C_{above} = 6.789 \times e^{0.0054 \times MAP} (R^2 = 0.7)$$

$$C_{below} = 28 \times MAT + 398 \ (R^2 = 0.47)$$

$$C_{Soil} = 3.3968 \times MAP + 3996.1 (R^2 = 0.11)$$

Where, C_{above} represents aboveground carbon pool data, $\boldsymbol{C_{below}}$ represents belowground carbon pool data based on precipitation and temperature. C_{Soil} represents the soil organic carbon pool data (Figure S3). MAP and MAT are the means of average annual precipitation (mm) and temperature (°C) each province between 2002 and 2020. The final carbon pool data can be calibrated as follows:

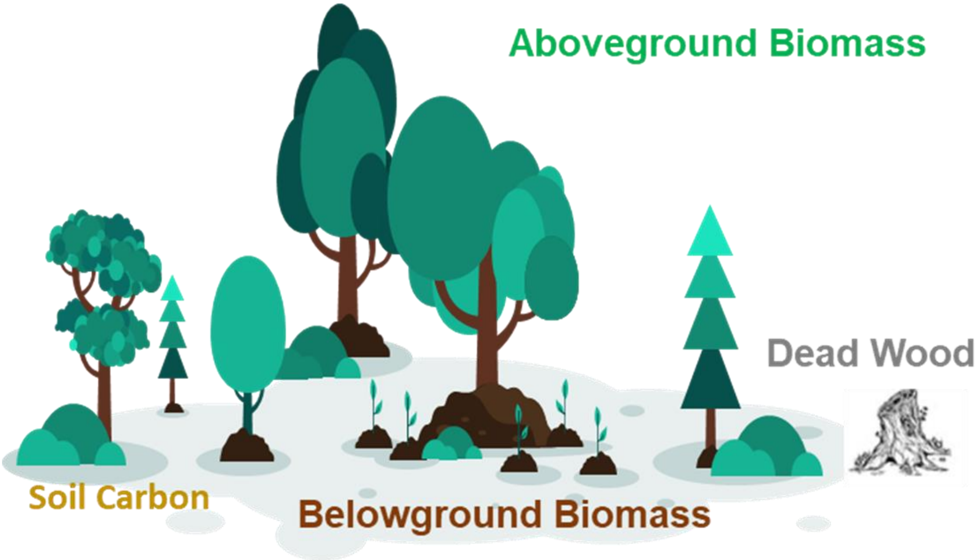
$$K_{BP} = \frac{C'_{above_i}}{C''_{above_i}}$$

$$K_{BT} = \frac{C'_{below_i}}{C''_{below_i}}$$

$$K_B = K_{BP} \times K_{BT}$$

$$K_S = \frac{C'_{soil_i}}{C''_{soil_i}}$$

where K_{BP} and K_{BT} represent the correction coefficients for biomass carbon pool by precipitation and temperature in the province i. K_B and K_S represent correction coefficients for the biomass and soil organic carbon pool in the province i. C'_{above_i} and C''_{above_i} represent the correction aboveground carbon pool data and baseline aboveground carbon pool data in the province i by precipitation (MAP). Other similar expressions with similar meaning.



$$C_{total} = C_{above} + C_{below} + C_{soil} + C_{dead}$$

Figure S3. Carbon pool Schematic diagram.

Table S2. Mean temperature (*MAT*) and precipitation (*MAP*) in each province. We interpolate data from meteorological stations (covering 101 national stations)

Province	MAT (℃)	MAP (mm)
Anhui	16.2	1343.7
Sichuan	12.6	1006.0
Hubei	17.4	1172.3
Chongqing	17.8	1212.5
Hunan	18.3	1396.3
Jiangxi	19.1	1642.9
Yunnan	17.7	1008.8
Zhejiang	17.9	1536.5
Jiangsu	16.1	1107.0
Shanghai	17.4	1270.6
Guizhou	16.8	1136.4

Note: The parameter value calculation refers to IDW interpolation in ArcGIS 10.2 (Environmental Systems Research Institute, 2013)

Table S3. Carbon pool data of different LULC in Anhui (ton/ha).

LULC	C_{above}	C_{below}	C_{soil}	C_{dead}

Cropland	5.2	1.2	29	0
Grassland	1.5	3.8	32	0
Forest	24	7	58	0
Shrubs	4	5.4	24	0
Bareland	0	0.8	27.5	0
Impervious surface	0	0	0	0
Wetland	0	0	0	0
Water	0	0	0	0

Note: The parameter value setting refers to Intergovernmental Panel on Climate Change (IPCC), Zhao et al. (2021b), Ji et al. (2016), PIAO et al. (2004) and HU et al. (2006). It is challenge to obtain dead carbon (Lehmann and Kleber, 2015), and we can ignore it. The definition of carbon abandonment in this study only considers the conversion of cropland to natural vegetation (i.e. grassland, forest, shrubs and bareland).

Table S4. Carbon pool data of different LULC in Chongqing (ton/ha).

LULC	C_{above}	C_{below}	C_{soil}	C_{dead}
Cropland	4.6	2.5	30	0
Grassland	1.9	5	31	0
Forest	37	14.6	39.1	0
Shrubs	8	7.4	59	0
Bareland	0	0.8	36	0
Impervious surface	0	0	0	0
Wetland	0	0	0	0
Water	0	0	0	0

Note: The parameter value setting refers to Intergovernmental Panel on Climate Change (IPCC), Liu et al. (2016a), Xue et al. (2019), Chen et al. (2022).

Table S5. Carbon pool data of different LULC in Guizhou (ton/ha).

LULC	C_{above}	C_{below}	C_{soil}	C_{dead}
Cropland	0.36	0.1	4.67	0
Grassland	0.11	0.46	4.64	0
Forest	2	1.79	5.91	0
Shrubs	0.80	0.74	7.04	0
Bareland	0	0.08	3.1	0
Impervious surface	0	0	0	0

Wetland	0	0	0	0
Water	0	0	0	0

Note: The parameter value setting refers to Intergovernmental Panel on Climate Change (IPCC), Han and Dong (2017), Feng et al. (2015), Ding et al. (2015).

Table S6. Carbon pool data of different LULC in Hubei (ton/ha).

LULC	C_{above}	C_{below}	C_{soil}	C_{dead}
Cropland	3.8	1.8	38.2	0
Grassland	1.9	4	42	0
Forest	20	17.9	53.8	0
Shrubs	8	7.4	26	0
Bareland	0	0.8	18	0
Impervious surface	0	0	0	0
Wetland	0	0	0	0
Water	0	0	0	0

Note: The parameter value setting refers to Intergovernmental Panel on Climate Change (IPCC), Tang et al. (2020), Miao et al. (2022), Yu et al. (2007), Houghton and Hackler (2003).

Table S7. Carbon pool data of different LULC in Hunan (ton/ha).

LULC	C_{above}	C_{below}	C_{soil}	C_{dead}
Cropland	4.2	1.7	48.2	0
Grassland	1.9	4	42	0
Forest	16	27.9	53.8	0
Shrubs	7	5.4	25.6	0
Bareland	0	0.8	26	0
Impervious surface	0	0	0	0
Wetland	0	0	0	0
Water	0	0	0	0

Note: The parameter value setting refers to Intergovernmental Panel on Climate Change (IPCC), Hu et al. (2021), Li et al. (2015), Liu et al. (2016b).

Table S8. Carbon pool data of different LULC in Jiangsu (ton/ha).

LULC	C_{above}	C_{below}	C_{soil}	C_{dead}
Cropland	5.4	2	109.2	0
Grassland	1.2	3	124.8	0

Forest	23	8	127	0
Shrubs	5	3	32	0
Bareland	0	0.8	64.3	0
Impervious surface	0	0	0	0
Wetland	0	0	0	0
Water	0	0	0	0

Note: The parameter value setting refers to Intergovernmental Panel on Climate Change (IPCC), Chuai et al. (2014), Chuai et al. (2011), Chuai and Huang (2011), Wang et al. (2010).

Table S9. Carbon pool data of different LULC in Jiangxi (ton/ha).

LULC	C_{above}	C_{below}	C_{soil}	C_{dead}
Cropland	4.6	1.2	33.4	0
Grassland	1	3	39.8	0
Forest	22	5	40.6	0
Shrubs	4	6.4	23	0
Bareland	0	0.8	27.5	0
Impervious surface	0	0	0	0
Wetland	0	0	0	0
Water	0	0	0	0

Note: The parameter value setting refers to Intergovernmental Panel on Climate Change (IPCC), Feng et al. (2022), Zhang et al. (2020), Li et al. (2011).

Table S10. Carbon pool data of different LULC in Shanghai (ton/ha).

LULC	C_{above}	C_{below}	C_{soil}	C_{dead}
Cropland	0.3	0.2	3.2	0
Grassland	0.12	0.30	2.65	0
Forest	2.3	0.8	3.15	0
Shrubs	0.50	0.12	3.2	0
Bareland	0	0	2.73	0
Impervious surface	0	0	0	0
Wetland	0	0	0	0
Water	0	0	0	0

Note: The parameter value setting refers to Intergovernmental Panel on Climate Change (IPCC), Li-jiang et al. (2010), Shen et al. (2020a), Han-lin et al. (2017).

Table S11. Carbon pool data of different LULC in Sichuan (ton/ha).

LULC	C_{above}	C_{below}	C_{soil}	C_{dead}
Cropland	5.6	1.1	29.4	0
Grassland	2.1	5.2	69.9	0
Forest	18	13	78	0
Shrubs	7.3	5.6	61	0
Bareland	0	0	16	0
Impervious surface	0	0	0	0
Wetland	0	0	0	0
Water	0	0	0	0

Note: The parameter value setting refers to Intergovernmental Panel on Climate Change (IPCC), Liu et al. (2006), Li et al. (2017), Xue et al. (2019), Luo (2009).

Table S12. Carbon pool data of different LULC in Yunnan (ton/ha).

LULC	C_{above}	C_{below}	C_{soil}	C_{dead}
Cropland	2.8	0.7	47.4	0
Grassland	0.4	2.6	72	0
Forest	26	13	56	0
Shrubs	8	7.2	12	0
Bareland	0	0	18	0
Impervious surface	0	0	0	0
Wetland	0	0	0	0
Water	0	0	0	0

Note: The parameter value setting refers to Intergovernmental Panel on Climate Change (IPCC), LI MQ and WU (2018), Tao et al. (2022), Duan et al. (2014), Lu et al. (2020).

Table S13. Carbon pool data of different LULC in Zhejiang (ton/ha).

LULC	C_{above}	C_{below}	C_{soil}	C_{dead}
Cropland	2	1.2	31	0
Grassland	0.6	0.6	35	0
Forest	21	6	71	0
Shrubs	2	1.2	29	0
Bareland	0	0	32	0

Impervious surface	0	0	0	0
Wetland	0	0	0	0
Water	0	0	0	0

Note: The parameter value setting refers to Intergovernmental Panel on Climate Change (IPCC), Zhu et al. (2019), Li et al. (2016c), Huang et al. (2014).

Supplementary information 3 : Temporal carbon accumulation and cumulative grain production

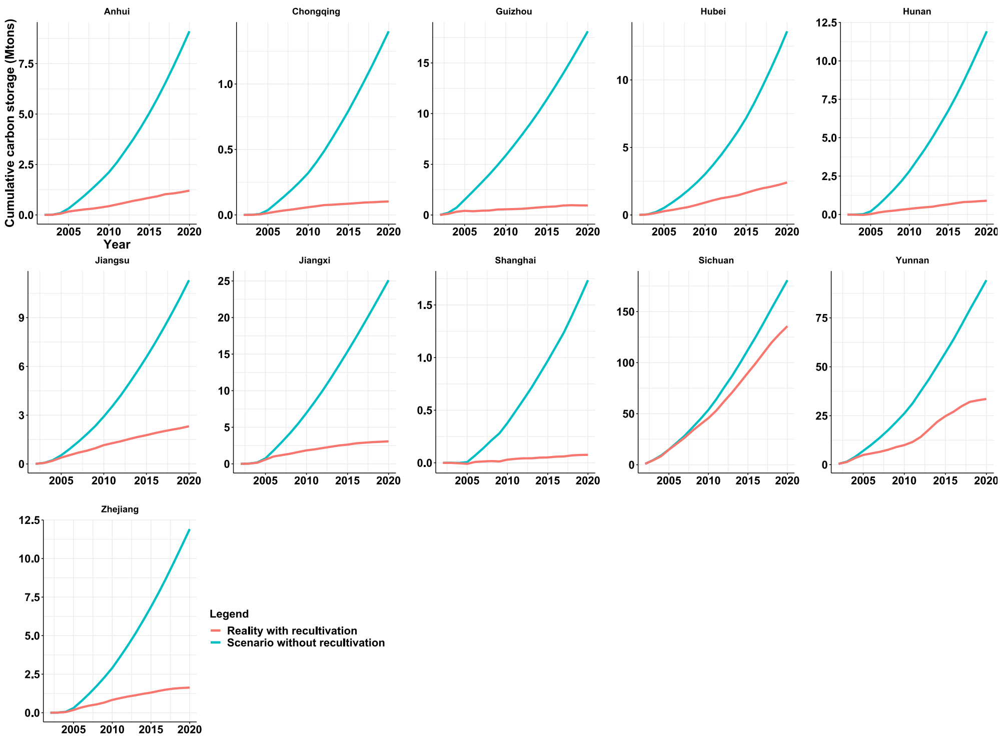


Figure S4. Cumulative carbon storage change following abandonment in each province over time, in terms of Mton C. The solid orange line represents the value in each province with real , and the solid red line represents the value, assuming a scenario without recultivation and other conversions.

Figure S5. Cumulative grain production change following abandonment in each province over time, in terms of Mton. The solid orange line represents the value in each province with real and the solide green line represents the value, assuming a scenario without recultivation and other conversions.

Table S14. Calories for different crops. We calculated the mean calorie of grain at the provincial scale based on the production-weighted method of different crops.

Crop type	Calorie (kcal/100g)
Rice	346
Wheat	317
Maize	335
Soybean	359
Potato	67
Rape	494

Supplementary information 4: Tradeoffs evaluation method selection

The method of correlation coefficient assessment depends on the normality and linear relationship of the two data sets. Pearson's correlation coefficient was used to describe the relationship between ecosystem services when the data were normally distributed and linearly correlated, otherwise Spearman's rank correlation coefficient was used

(Mouchet et al., 2014). Given the large sample size, we tested the normality and linearity of the data on carbon stock change and grain yield change using generalised quantity-quantity plots (Q-Q plots) (Wilk and Gnanadesikan, 1968) and scatter plots. Here, we randomly selected the test results of Sichuan in 2019-2020 as an example.

Figures S6 and S7 show the normality tests for the carbon stock change and grain yield data, respectively. From the Q-Q plot (Q-Q plot) test of carbon stock changes, we found that the data were not consistent with the 45° line, which implies that the data did not meet the requirement of normal distribution. We then tested the results with the Shapiro-Wilk normality test (Shapiro and Wilk, 1965). The results of the test showed the statistic $W = 0.48$, $p < 2.2e-16$, indicating that the entire data set did not conform to a normal distribution. Similarly, the distribution of the data regarding changes in grain yields is closer to a straight line relative to the previous plot. However, after performing the Shapiro-Wilk normality test, we found that the statistic $W = 0.87$, $p = 0.008$ for the yield change data, indicating that it did not meet the criteria for a normal distribution.

Figure S8 shows the scatter linear fit, and we can clearly see that there is no linear relationship between the two sets of data. Therefore, we chose to use the Spearman test to calculate the correlation coefficient between the two variables.

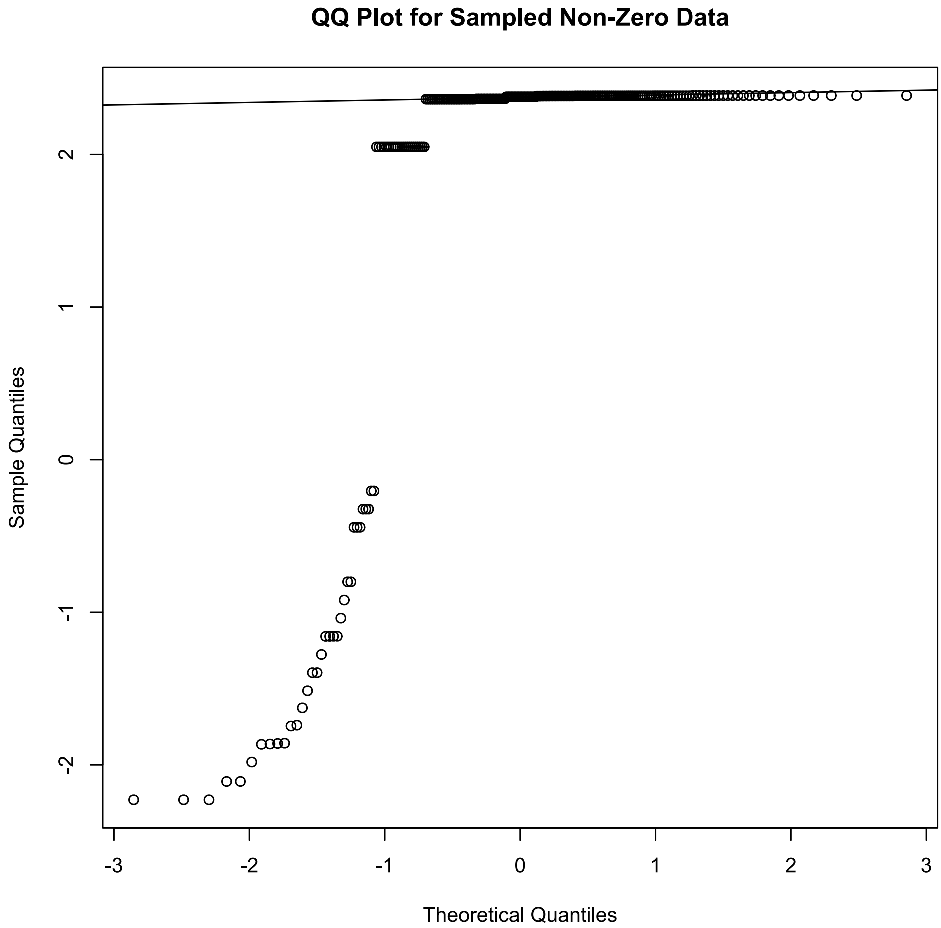


Figure S6. Q-Q plot of carbon stock change normal test. We standardised and did the normality test using R software (version: 4.1.3).

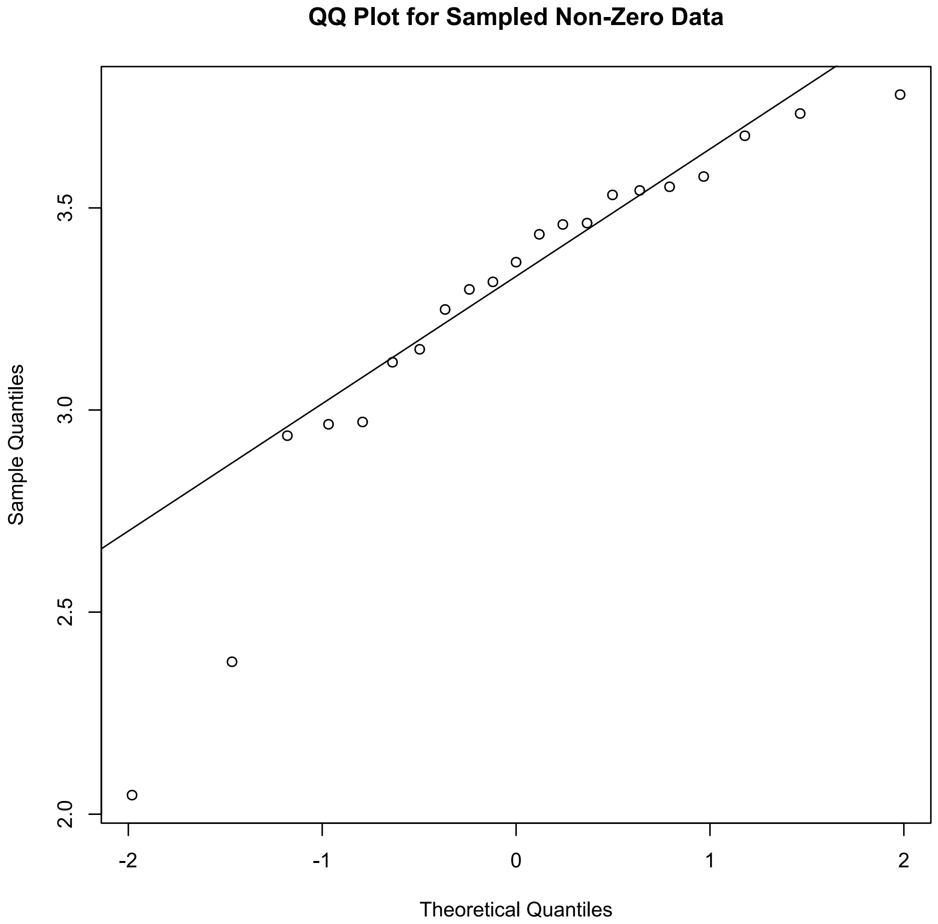


Figure S7. Q-Q plot of grain yield change normal test. We standardised and did the normality test using R software (version: 4.1.3).

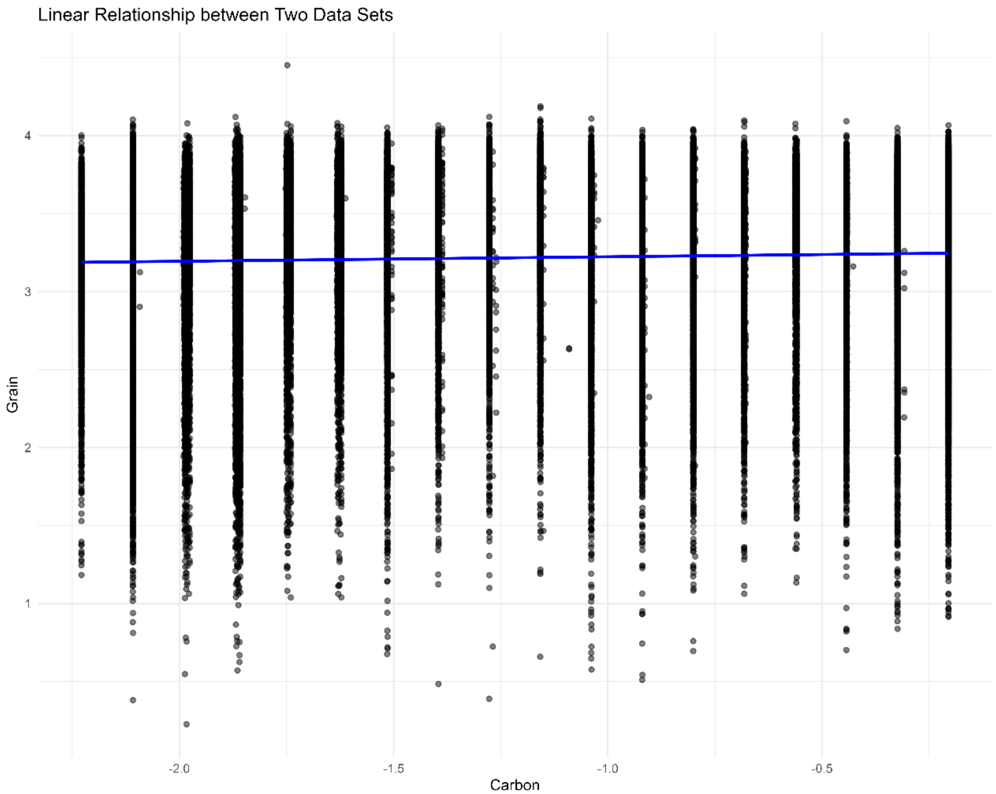


Figure S8. Linear scatterplot of carbon stock change and grain yield change. The blue line is the fitted line. We standardised and did the normality test using R software (version: 4.1.3).

Supplementary information 5: Spatial pattern of correlation coefficient of province

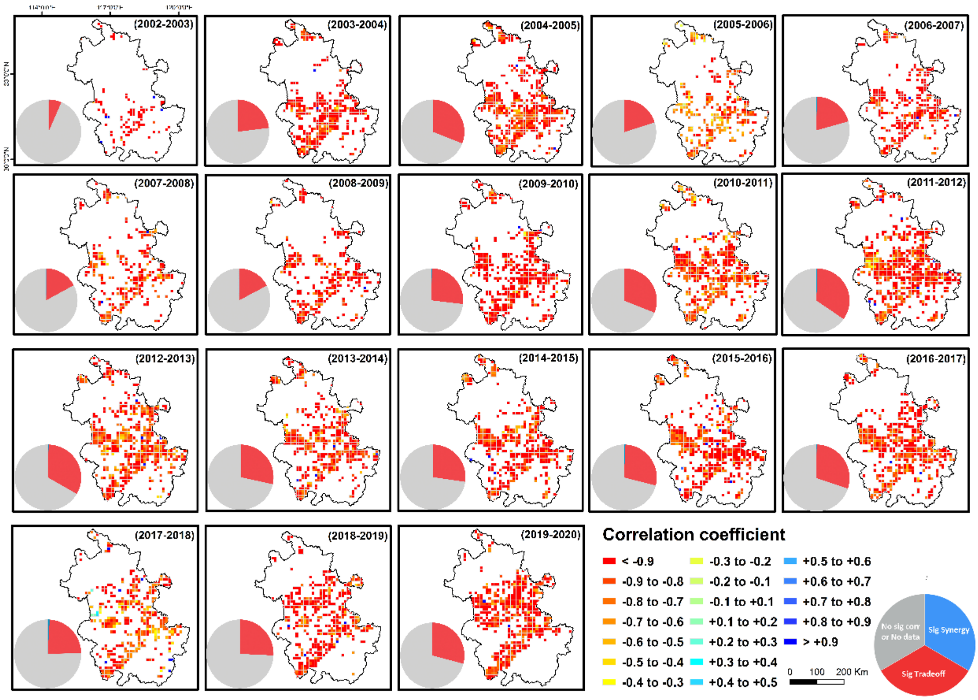


Figure S9. Spatial pattern of correlation coefficient (p <0.05) bewteen carbon stock change and grain yield change in Anhui (resoultion: 10×10 km). 2002-2003 indicates the period of 2002-2003, others are similar. The pie chart in the buttom left represents the proportion of the number of grids in different categories, where significant trade-offs (red slices), significant synergies (blue), no significant correlation or no data (grey).

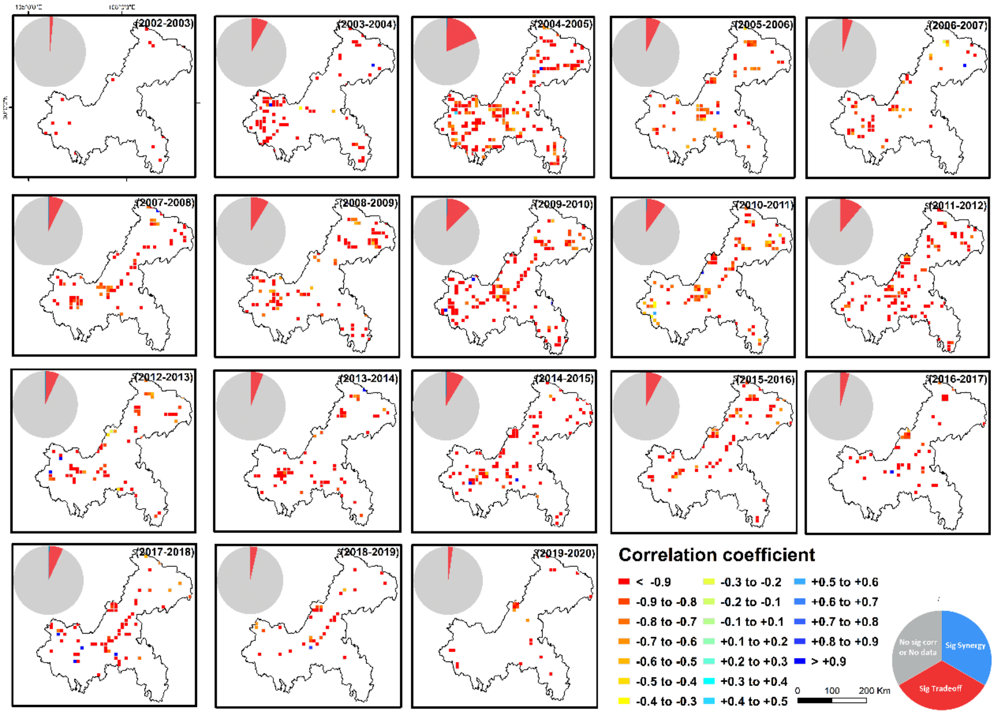


Figure S10. Spatial pattern of correlation coefficient (p <0.05) bewteen carbon stock change and grain yield change in Chongqing (resoultion: 10×10 km). 2002-2003 indicates the period of 2002-2003, others are similar. The pie chart in the top left represents the proportion of the number of grids in different categories, where significant trade-offs (red slices), significant synergies (blue), no significant correlation or no data (grey).

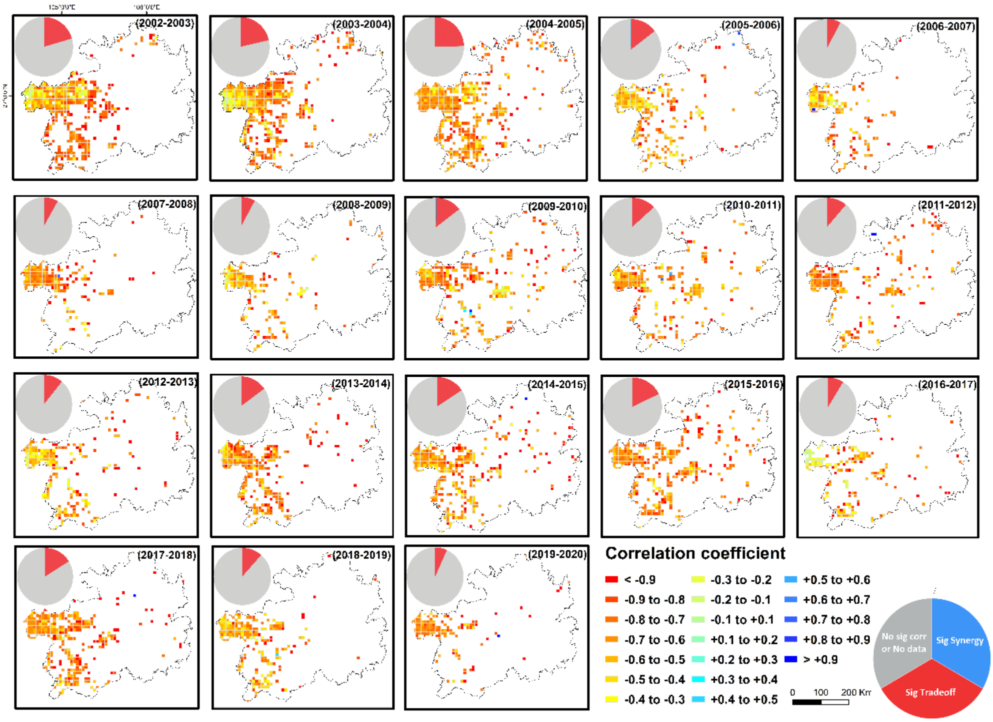


Figure S11. Spatial pattern of correlation coefficient (p <0.05) bewteen carbon stock change and grain yield change in Guizhou (resoultion: 10×10 km). 2002-2003 indicates the period of 2002-2003, others are similar. The pie chart in the top left represents the proportion of the number of grids in different categories, where significant trade-offs (red slices), significant synergies (blue), no significant correlation or no data (grey).

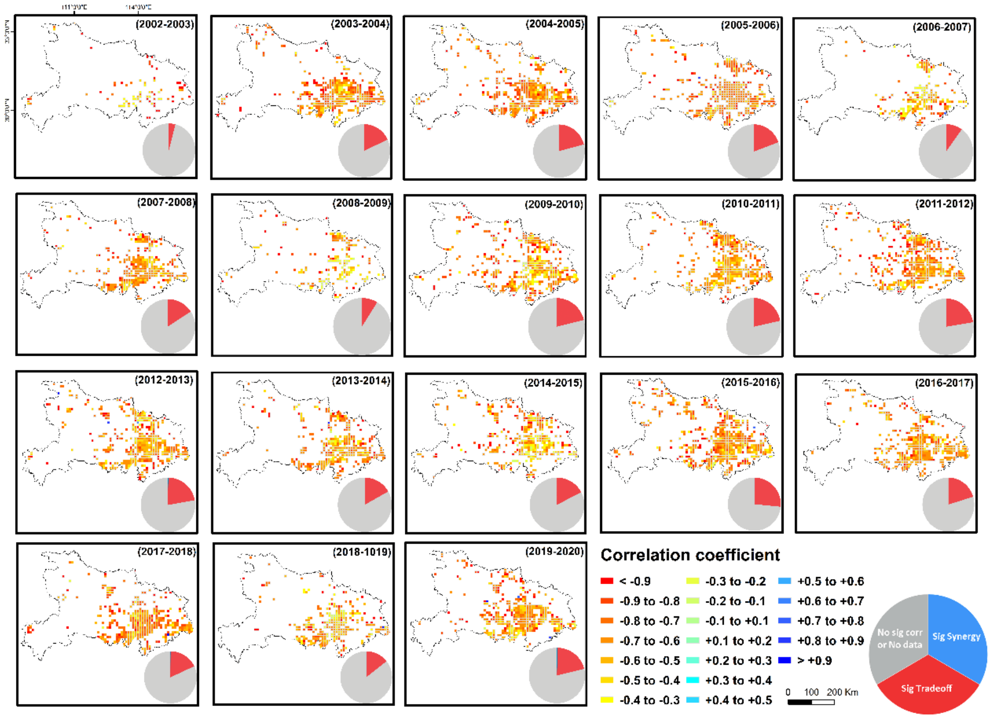


Figure S12. Spatial pattern of correlation coefficient (p <0.05) bewteen carbon stock change and grain yield change in Hubei (resoultion: 10×10 km). 2002-2003 indicates the period of 2002-2003, others are similar. The pie chart in the bottom right represents the proportion of the number of grids in different categories, where significant trade-offs (red slices), significant synergies (blue), no significant correlation or no data (grey).

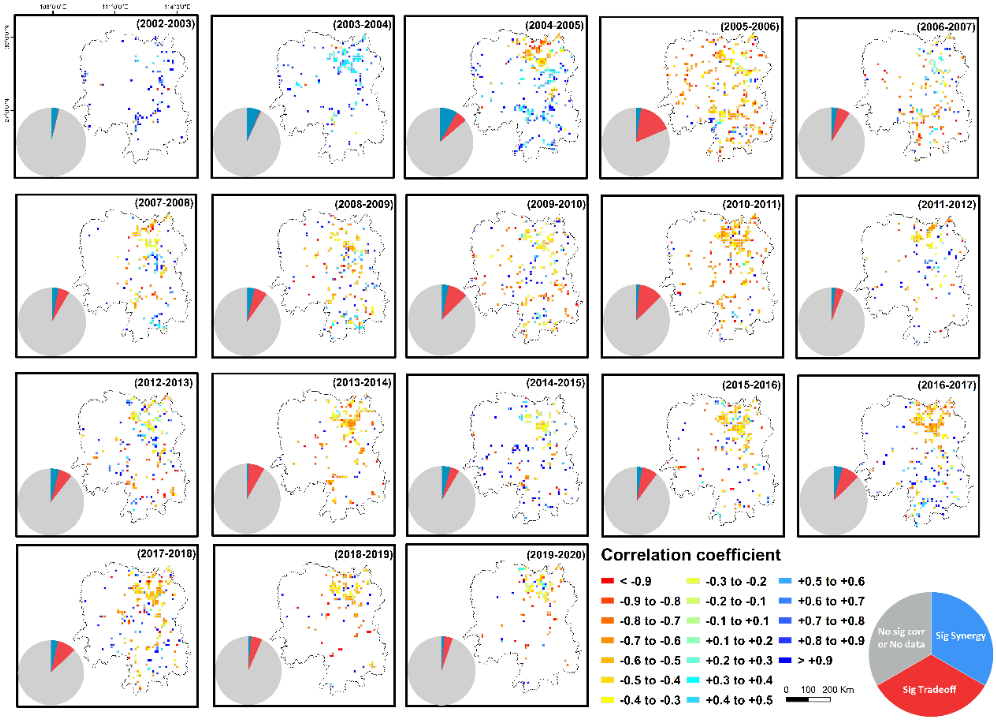


Figure S13. Spatial pattern of correlation coefficient (p <0.05) bewteen carbon stock change and grain yield change in Hunan (resoultion: 10×10 km). 2002-2003 indicates the period of 2002-2003, others are similar. The pie chart in the bottom left represents the proportion of the number of grids in different categories, where significant trade-offs (red slices), significant synergies (blue), no significant correlation or no data (grey).

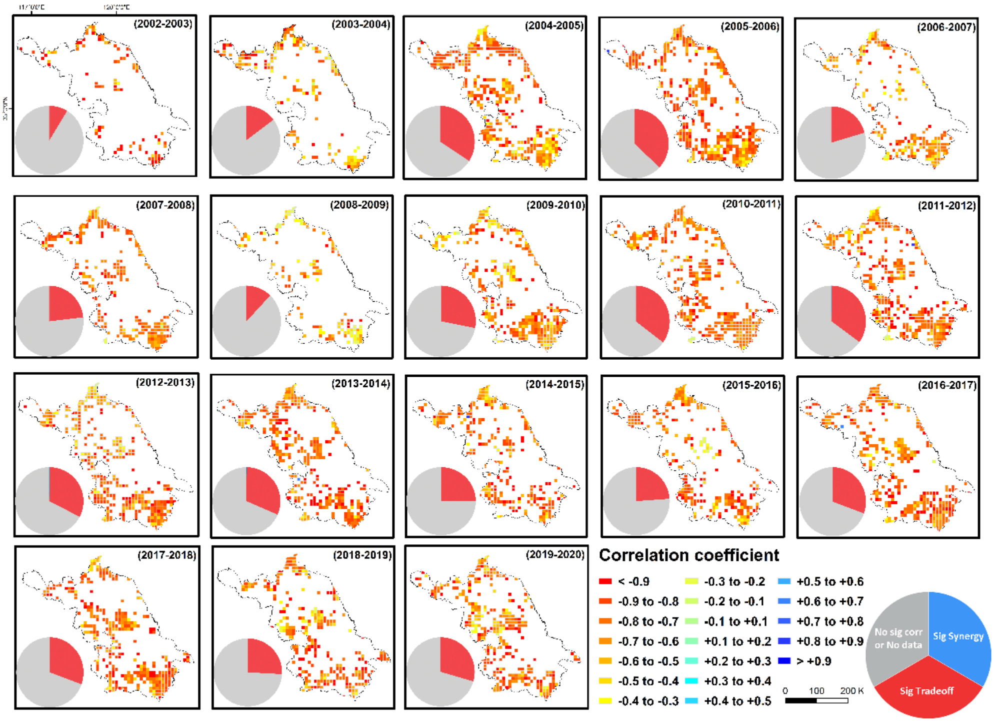


Figure S14. Spatial pattern of correlation coefficient (p <0.05) bewteen carbon stock change and grain yield change in Jiangsu (resoultion: 10×10 km). 2002-2003 indicates the period of 2002-2003, others are similar. The pie chart in the bottom left represents the proportion of the number of grids in different categories, where significant trade-offs (red slices), significant synergies (blue), no significant correlation or no data (grey).

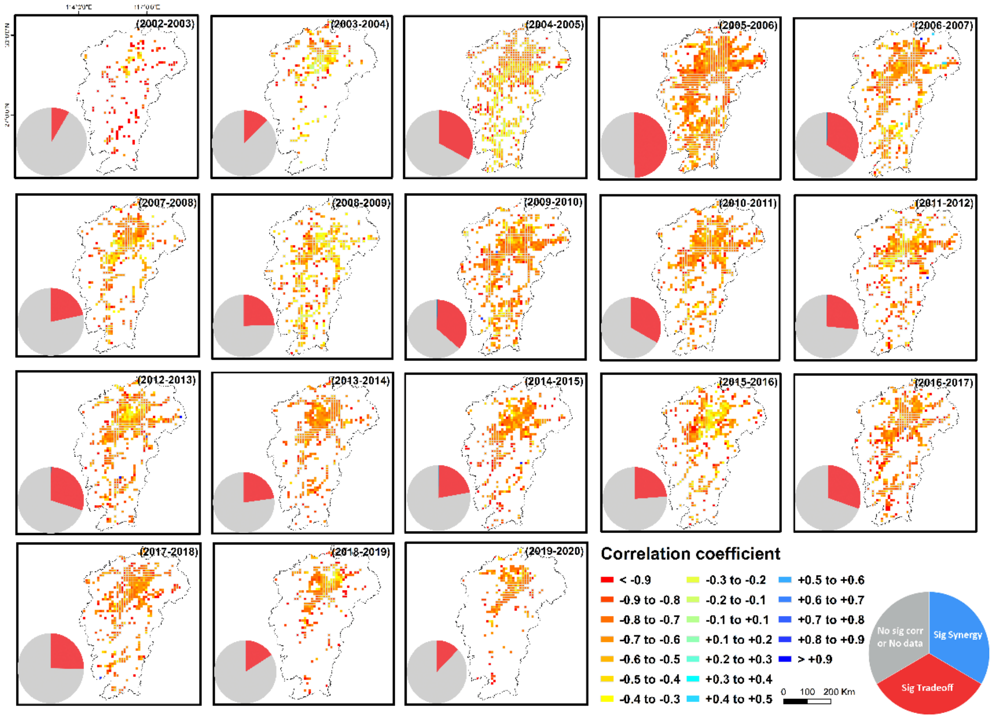


Figure S15. Spatial pattern of correlation coefficient (p <0.05) bewteen carbon stock change and grain yield change in Jiangxi (resoultion: 10×10 km). 2002-2003 indicates the period of 2002-2003, others are similar. The pie chart in the bottom left represents the proportion of the number of grids in different categories, where significant trade-offs (red slices), significant synergies (blue), no significant correlation or no data (grey).

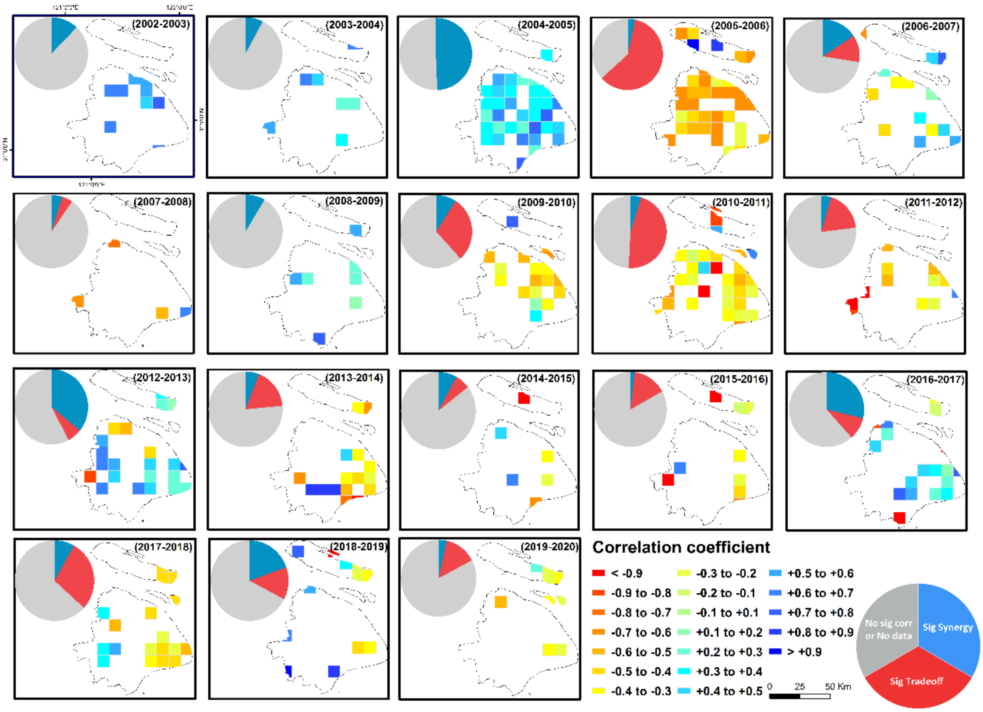


Figure S16. Spatial pattern of correlation coefficient (p <0.05) bewteen carbon stock change and grain yield change in Shanghai (resoultion: 10×10 km). 2002-2003 indicates the period of 2002-2003, others are similar. The pie chart in the top left represents the proportion of the number of grids in different categories, where significant trade-offs (red slices), significant synergies (blue), no significant correlation or no data (grey).

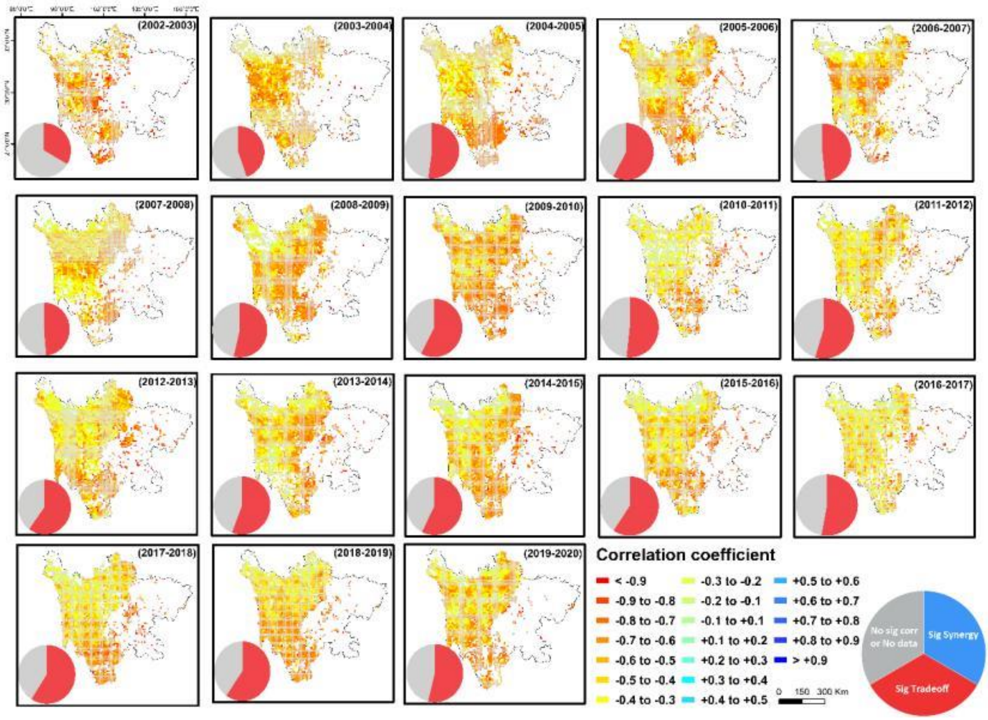


Figure S17. Spatial pattern of correlation coefficient (p <0.05) bewteen carbon stock change and grain yield change in Sichuan (resoultion: 10×10 km). 2002-2003 indicates the period of 2002-2003, others are similar. The pie charts in the bottom left represents the proportion of the number of grids in different categories, where significant trade-offs (red slices), significant synergies (blue), no significant correlation or no data (grey).

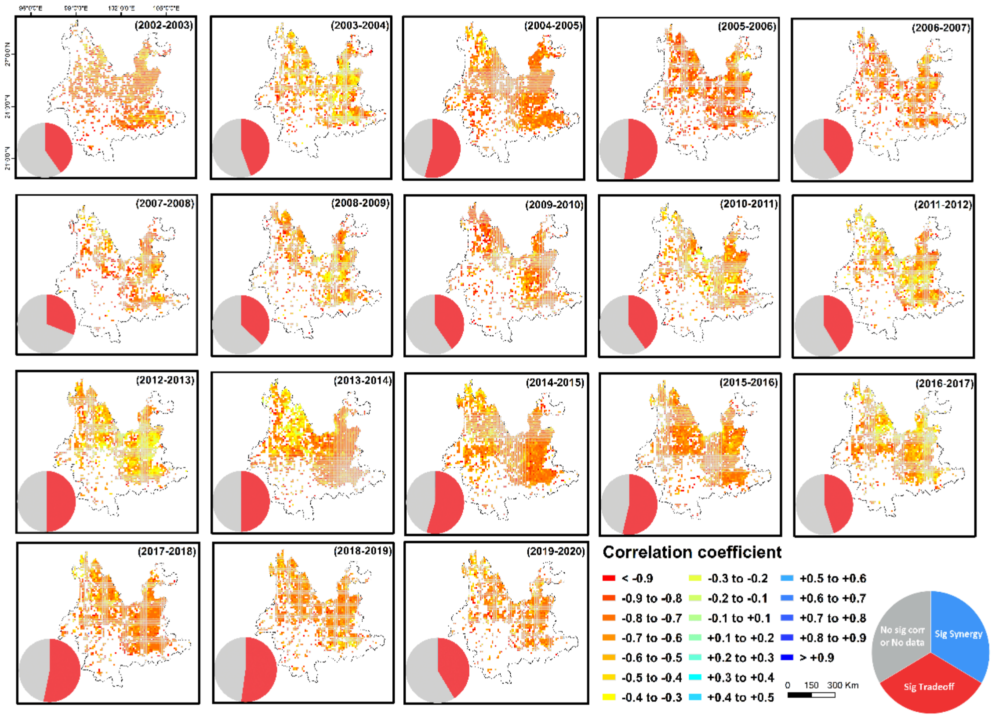


Figure S18. Spatial pattern of correlation coefficient (p <0.05) bewteen carbon stock change and grain yield change in Yunnan (resoultion: 10×10 km). 2002-2003 indicates the period of 2002-2003, others are similar. The pie chart in the bottom left represents the proportion of the number of grids in different categories, where significant trade-offs (red slices), significant synergies (blue), no significant correlation or no data (grey).

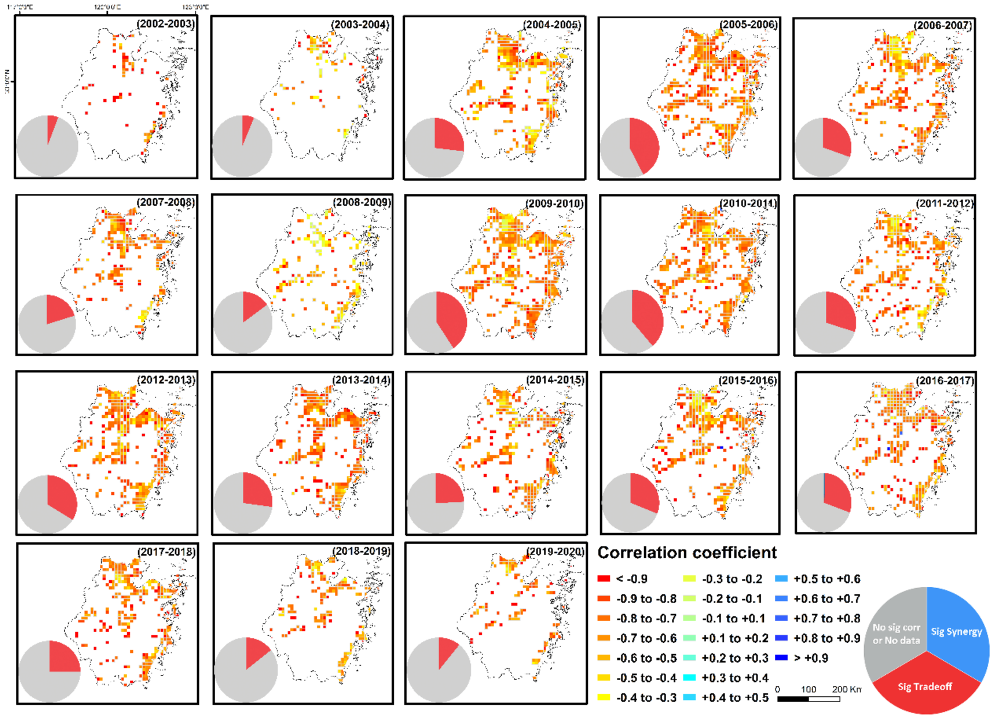


Figure S19. Spatial pattern of correlation coefficient (p <0.05) bewteen carbon stock change and grain yield change in Zhejiang (resoultion: 10×10 km). 2002-2003 indicates the period of 2002-2003, others are similar. The pie chart in the bottom left represents the proportion of the number of grids in different categories, where significant trade-offs (red slices), significant synergies (blue), no significant correlation or no data (grey).

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Doctoral training (60 credits)

1. THEMATIC TRAINING (17 credits)

- Course in CAAS
- Zen-thesis: working and communicating with your PhD supervisor
- Zen-Thesis: I write my thesis on a daily basis

2. TRANSVERSAL TRAINING (11 credits)

- International Webinar on CAAS: How to monitor cropland abandonment
- Erasmus + KA2 AGreenSmart: Agriculture and Animal husbandry in Belgium: A case of the dairy farm "Le Bailli". Lille, France. (Oral presentation)
- France-Belgium AgriTech meeting, Gembloux Agro-Bio Tech, Belgium
- International Webinar on Gembloux Agro-Bio Tech: INAUGURATION SERRE EN TOITURE
- Research project discussion with Committee, CAAS, China.

3. SEIENTIFIC COMMUNICATION (32 credits)

- Cropland abandonment across the Yangtze River Basin does provide only limited benefits for C sequestration. EGU 2023. (Oral presentation)
- Abandoned cropland recultivation across the Yangtze River Basin does alleviated regional food insecurity. Belgian Geographers Day 2024. (Poster presentation)
- Mapping the spatiotemporal dynamics of cropland abandonment and recultivation across the Yangtze River Basin. Day of the Young Soil Scientist 2024. (Poster presentation)
- Mapping the Spatiotemporal Dynamics of Cropland Abandonment and Recultivation across the Yangtze River Basin. (Peer-reviewed paper)
- An In-Depth Assessment of the Drivers Changing China’s Crop Production Using an LMDI Decomposition Approach. (Peer-reviewed paper)