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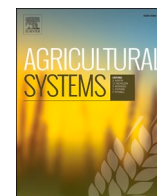
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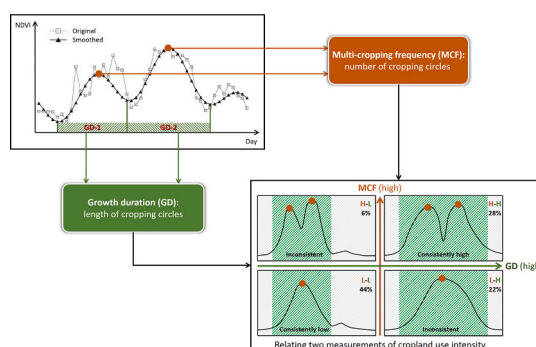
The complexity of measuring cropland use intensity: An empirical study

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HIGHLIGHTS

- Cropland use intensity can be measured by various indicators which are not always coherent and consistent.
- We hypothesized that cropland use intensity measured by different indicators may differ.
- We found that about 28% of croplands displayed inconsistent intensity in a case study.
- The substantial inconsistency indicates that measuring and interpreting cropland use intensity are equally important.
- We need to better understand the multidimensionality of cropland intensification for distinct policy measurements.

GRAPHICAL ABSTRACT



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ABSTRACT

CONTEXT: Cropland intensification promises additional food supply without further expanding croplands into natural ecosystems. Cropland use intensity measures the degree of intensification by various indicators, both from input and output perspectives; all of these indicators are however not always coherent—which may cause confusion and send contradicting signals to policymakers. Few empirical studies have been conducted to relate and compare various intensity indicators.

OBJECTIVE: In this study, we start with a hypothesis that cropland use intensity measured by different indicators may differ. We then test such a hypothesis based on empirical evidence in a typical multi-cropped region (i.e., Jinxian County) in Jiangxi Province—a major breadbasket in Southern China.

METHODS: We focus on two widely used indicators, i.e., multi-cropping frequency (MCF) and crop growth duration (GD_a), measured by a hybrid time-series remote sensing dataset which fuses MODIS and Gaofen-1 images for the year 2015. We map these two indicators independently at a 16 m spatial resolution. For each pixel, MCF takes value from 1 to 3 corresponding to single-, double- and triple- cropping; while GD_a is quantified by the accumulative crop growth days within the study year. We relate the values of two indicators, summarize the descriptive statistics of GD_a grouped by MCF categories, and compare MCF and GD_a values by using a box-whisker chart, a bivariate map, and a set of statistical tests.

RESULTS AND CONCLUSIONS: We find that a significant overlap of GD_a exists between single cropping and double cropping both visually and statistically. In other words, the different cropland intensity levels measured

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by MCF appear to be the same if measured by GD_a . The box-whisker chart shows that the GD_a of single cropping in the upper quarter is substantially longer than the GD_a of double cropping in the lower quarter. The non-parametric tests show that the overlapped GD_a between single cropping and double cropping exists substantially, which may cause confusion. Moreover, the bivariate map shows that single cropping with shorter growth duration (i.e., consistent low intensity) and double cropping with longer growth duration (i.e., consistent high intensity) account for 44% and 28%, respectively, while the rest manifested as inconsistent which accounts for another 28% of the total cropland area.

SIGNIFICANCE: These results confirm our hypothesis—the inconsistency among intensification indicators. Different measurements may convey contradicting messages for policymakers in pursuing the sustainable intensification goals, which suggests more efforts are required to understand the multidimensionality of the process of cropland intensification for distinct policy measurements.

1. Introduction

Although global food production has increased dramatically in the past few decades, there are still about 821 million people suffering from hunger (FAO, 2018). More food still needs to be produced to increase global food security, especially under the current COVID pandemic (Laborde et al., 2020; Stephens et al., 2020). This undoubtedly brings more pressure on agriculture to further increase production, which requires either expanding cropland into nature areas or intensifying the existing use of cropland (Wu et al., 2014). However, it is environmentally costly to further expand cropland, because virtually all the global suitable area for agriculture has already been fully used and the global cropland area is approaching the planetary boundary (Henry et al., 2018; Rockström et al., 2017). Constantly infringing agriculture into natural areas, such as tropical forests, comes at a hefty price, e.g. carbon emission (Baumann et al., 2017), adverse effects on local climate (Silvério et al., 2015), and loss of biodiversity (Kehoe et al., 2017; Zabel et al., 2019). Even the reclamation of abandoned cropland, e.g., in the former Soviet Union countries, could provide extra food. But it will release the sequestered carbon as well (Meyfroidt et al., 2016; Schierhorn et al., 2014). Consequently, most of the additional food production will have to come from cropland intensification, i.e., more food production per unit of land (Charles et al., 2014; Stephens et al., 2018; Wu et al., 2014).

Comparing to the straightforward process of cropland expansion, the concept of cropland intensification is much more complicated (Erb et al., 2013; Hu et al., 2020; Struik and Kuyper, 2017). Literally, cropland intensification indicates any process that could result in an increase in land productivity, i.e., the total output per unit of land. While the increase in land productivity is a goal of cropland intensification, the process to achieve it includes various human management activities, ranging from the adoption of multiple cropping, the substitution of cultivars, to the application of irrigation and fertilizers (Hu et al., 2020). Cropland use intensity has been conceptualized to manifest the degree of intensification, which is usually measured by two aspects: from the output perspective, it stresses the consequence of intensification—the increase of production; while from the input perspective, it emphasizes the process itself—the intensified human management activities (Erb et al., 2013). In some cases, cropland use intensity is measured by the final output of production especially when the increase of food supply is most concerned (Niedertscheider et al., 2016; Pei et al., 2015). In other cases, intensification is measured in terms of cropping intensity (Iizumi and Ramankutty, 2015), irrigation intensity (Malek et al., 2018), fertilizer intensity (Kong et al., 2014), and crop duration (Siebert et al., 2010).

Facing the grand challenge of global food security, the output-based intensity receives more attention. However, intensification needs solutions from the input side, otherwise discussing the output-based intensity is meaningless. There are a few existing studies that have assessed the opportunities for intensification, which are largely manifested by the measurements of input-based cropland use intensity (Hunter et al., 2017; Mauser et al., 2015; Scherer et al., 2018). For example, many people believe that increasing cropping intensity will be

a direct and effective way for cropland intensification because the yield-based intensity emphasizes the production per unit per single season while cropping intensity considers the accumulated intensification effect that the end-year harvested area, as well as final production, will be increased by adding another crop after the previous crop was harvested (Yu et al., 2017). With the development of remote sensing technology and data availability, it is increasingly feasible to measure cropping intensity for a larger geographical area. Remote sensing, thus, has been widely used to measure cropland use intensity from the input perspective (Estel et al., 2016; Liu et al., 2020b; Liu et al., 2020a; Xiang et al., 2019; Yan et al., 2019). According to Wu et al. (2018), there is a large proportion of existing croplands worldwide (ca. 30%) have harvested less frequently than it could be under the climate and other biophysical conditions, and therefore, the global cropping intensity gap leaves great potential for cropland intensification. The increase of cropping intensity, could potentially provide a substantial food supply – up to 50% of the current production – without expanding any cropland (Ray and Foley, 2013).

The multi-faceted nature of cropland intensification requires comprehensive measures; however, few existing studies have measured it systematically with multiple metrics. For example, most of the existing studies focused on cropping intensity, while ignoring other measurements, e.g. crop duration (Siebert et al., 2010; Waha et al., 2020). Each individual crop requires a growth duration (GD) to reach maturity (Ritchie and Nesmith, 1991), which differs greatly among cultivars (e.g. the GD of food crops could range between 60 and 250 days). Generally, longer GD cultivars would have a higher yield than that of shorter GD cultivars, because more light energy will be absorbed through photosynthesis during the longer growth period (Fang et al., 2019; Liu et al., 2013). This implies that substituting shorter GD crops with longer GD crops is also an alternative to gain the accumulated intensification effect. Comparing with cropland use intensity measured by the number of harvests, GD as a continuous variable, can better reflect the variance in annual production. Yet, few large-scale intensification assessments based on GD have been conducted due to limited observational techniques.

Moreover, different intensification measurements might lead to different understandings. For example, in the global agricultural regions where multiple cropping is potentially possible, adopting multiple cropping would not only increase cropping intensity, but also likely prolong the year-round accumulative crop duration. Yet in other cases, substituting longer GD crops for a single season would occupy the room for the following crops in the same year, hence might leave no possibility for further increasing cropping intensity. In some extreme cases, the GD of one long-season crop might be even longer than the accumulated GD of two shorter-season crops. It suggests that cropping intensity and crop duration could have both positive and negative correlations, despite the adoption of multiple cropping and the substitution of longer GD cultivars are both intensification measurements. According to Waha et al. (2020), the global harvested area gap is lower than Wu et al. (2018)'s estimation: the former regarded crop duration as the prioritized intensification measurement which would in turn affect the increase of the cropping intensity, while the priority for the latter was cropping

intensity per se.

Given such a phenomenon may substantially exist as farmers make different crop choices, we hypothesize that a higher cropland use intensity measured by one indicator is not necessarily interpreted as high by the other. However, the direct assessments for different intensification alternatives are rare, and the possible confusion induced by different measurements of intensity is largely unknown. In this study, we conduct an empirical analysis in a traditional multi-cropped agricultural area in Southern China to test this hypothesis and to better understand how different manifestations of cropland use intensity are spatially variated. We focus on the adoption of multiple cropping and the substitution of cultivars for the current study, not only because they are both key measurements for cropland intensification, but also due to the advances in earth observation which allows for reliable estimation of these two metrics at scale comparing to the irrigation and fertilizer intensity (Bégué et al., 2018; Weiss et al., 2020). Moreover, focusing on limited measurements would simplify the representation of complexity, which is also a consideration for such a pilot study. By doing so, we hope to raise the awareness of the multi-faceted nature of intensification, before further carrying out more systematic assessments regarding the trade-offs and synergies of different cropland intensification alternatives.

2. Conceptual framework

We propose a framework that integrates the characterization of cropland use intensity from two aspects, i.e., the adoption of multiple cropping and the substitution of cultivars, to enable a comparison focusing on their consistencies and variations. To do so, we adopt the multi-cropping frequency (MCF) observed by remote sensing imagery for the former aspect, which measures multi-cropping at a finer scale than the multi-cropping index (MCI) (Xiang et al., 2019). We also use the same remote sensing imagery for the latter aspect. We capture the GD

reflected by the cropland phenological information, which enables a regional-level and full-coverage observation, rather than recording the crop performance at limited field sites. We first map these indicators independently and then compare them systematically (Fig. 1).

We use the smoothed NDVI (Normalized Difference Vegetation Index) curve to present the crop growth throughout a year (Fig. 1, upper-left box), which is a widely adopted approach for crop growth monitoring (Bégué et al., 2018; Weiss et al., 2020). Subsequently, we determine the MCF by counting the number of peaks (Fig. 1, highlighted in orange), and estimate the GD by summing the number of days between two consecutive troughs of the same curve (Fig. 1, highlighted in green). Given the case of multi-cropping, the year-end GD_a is calculated by adding up the crop-specific GDs. We apply a 2×2 quadrant to represent the possible confusion induced by different measurements of cropland use intensity (Fig. 1, lower-right box). The confusing effect is illustrated by two circumstances, i.e., higher MCF with shorter GD_a , and lower MCF with longer GD_a , which are plotted in the second quadrant and the fourth quadrant, respectively.

3. Materials and methods

3.1. Study area

The data applied in the current study are largely yielded from our recent researches in Jinxian County, Jiangxi Province, South China. Located at the south bank of Poyang Lake, the largest freshwater lake in China, Jinxian County has the potential for triple-cropping owing to favorable climate conditions (Xiang et al., 2019). Jinxian County's actual cropland use intensity is also relatively high: it has been recognized as a key grain production region (The State Council, 2019). We deliberately chose a small study area to make sure the cropping systems are not varied significantly. In this case, we could assume that the contradicting observations of cropland use intensity are only caused by

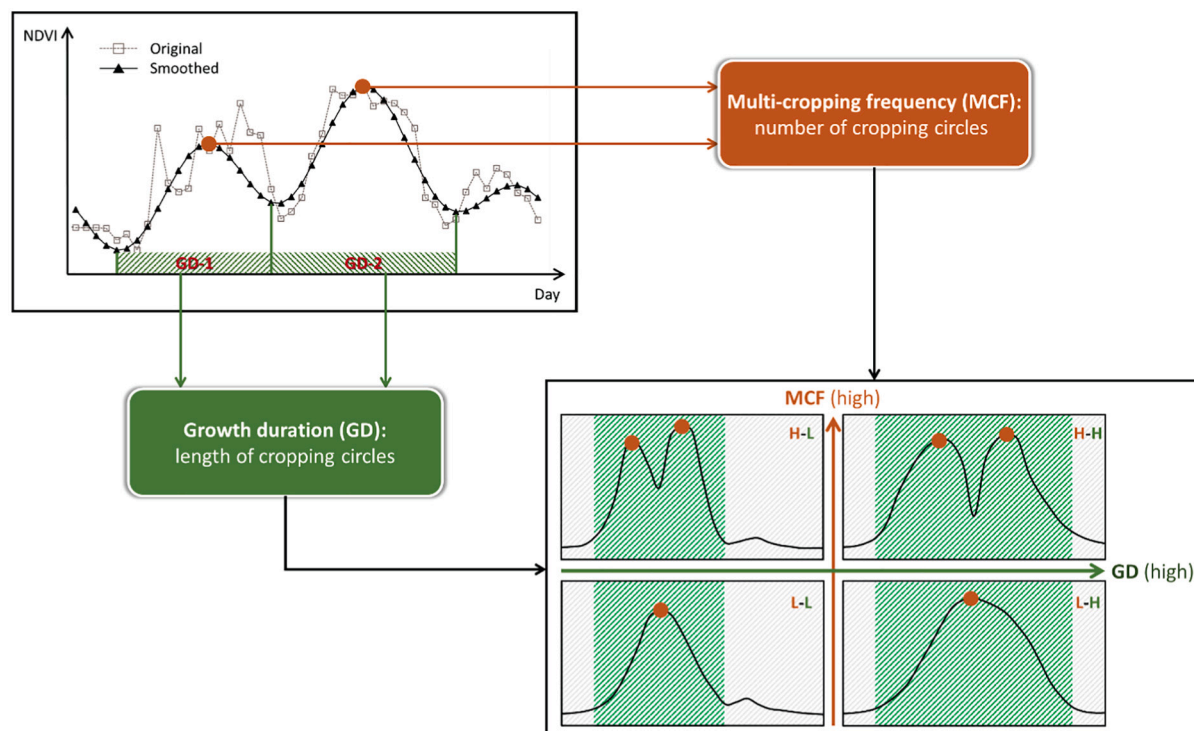


Fig. 1. Conceptual framework of mapping and comparing the year-end MCF and GD_a . The upper-left figure is an illustration of mapping MCF and GD_a by time-series remote sensing images, which is modified from Yan et al. (2019). The lower-right figure is an illustration of possible confusion (e.g., the H-L and L-H in the second and fourth quadrant, respectively) when adopting both indicators for measuring cropland use intensity. The color scheme, i.e., orange and green, represents the measurements of MCF and GD_a respectively.

human decisions (e.g., crop choice) rather than determined by the varied biophysical characteristics. Although the analysis is in a local context, the methods of the analysis can be used in other places where multiple cropping is feasible.

3.2. MCF mapping

In Xiang et al. (2019), we developed a GF-MODIS dataset by fusing MODIS Terra data product (MOD09Q1) and Gaofen-1 (GF-1, Chinese high-resolution remote sensing satellite) Wide Field of View (WV) images, and obtained the smoothed NDVI curve by using the Harmonic Analysis of Time Series method (HANTS). The hybrid dataset has a spatial resolution of 16 m and a temporal resolution of 8d, based on which we successfully mapped the MCF in the year 2015 with substantially higher accuracy than the MCF maps solely produced by MODIS or GF-1.

3.3. GD mapping

Based on the GF-MODIS dataset developed for the year 2015, we apply the proportional dynamic threshold method to measure the GD. The dynamic threshold method determines the thresholds of the smoothed NDVI curve by defining the times when NDVI increases and reduces according to the threshold values, which are further known as the start and end of growth duration respectively (Yu and Zhuang, 2006). By using the proportional dynamic threshold method the influence of different soil backgrounds and vegetation types can be eliminated (White et al., 2009). The thresholds are the lowest and highest values that can produce an effect, which is calculated as:

$$NDVI_{thre} = (NDVI_{max} - NDVI_{min}) \times C \quad (1)$$

where $NDVI_{max}$ is the maximum value in the entire NDVI curve, $NDVI_{min}$ is the minimum values in both the ascending and descending NDVI curves. C is an experimental parameter, which is set as 10%, 15%, and 20% for single-, double-, and triple-cropping, respectively (White et al., 2009; Yu and Zhuang, 2006).

For any pixel observed as single-cropping, the start-growing point of this curve is M_1 and the end-growing point is N_1 . Then the growth duration for the first crop (GD_1) is calculated by referring to the gap between M_1 and N_1 :

$$GD_1 = D_{M_1} - D_{N_1} \quad (2)$$

Analogically, the GD_n can be calculated where the pixels are multiple cropped. The year-end GD_a is calculated by summing up the crop-specific GD_s :

$$GD_a = \sum GD_n \quad (3)$$

3.4. Comparing MCF and GD_a

We compare MCF and GD_a by grouping the GD_a into different MCF categories. We qualitatively compare them by calculating the descriptive statistics of GD_a across MCF categories and by plotting them into a Box-Whisker Chart, with the x-axis (categories) representing the frequency and the y-axis (boxes and whiskers) representing the duration. We then conduct a few statistical tests to compare MCF and GD_a quantitatively – by adopting both parametric and non-parametric tests (Sheskin, 2003) – to explore whether the means, medians, distribution, and range of GD_a are significantly different across MCF categories. Finally, we develop an integrated characterization of cropland use intensity by setting threshold values for the 2×2 quadrant coordinates (Fig. 1) inferentially according to the statistical characteristics of the observational results.

4. Results

4.1. Maps for MCF and GD_a

Based on the hybrid GF-MODIS dataset, the map of MCF distribution is directly adopted from (Xiang et al., 2019) and is displayed in the left part of Fig. 2. The shares of single-cropping, double-cropping, and triple cropping are ca. 65%, 34%, and 1%, respectively. On the other hand, the spatial distribution of GD_a is mapped and displayed in the right part of Fig. 2. Visually, GD_a is valued between 60 days and 300 days across the entire study region. The majority of GD_a is between 120 days and 180 days with an approximative normal distribution. A concentrated pattern of high-value pixels in the south part demonstrates a relatively longer GD_a , while another concentrated pattern of low-value pixels in the northern part indicates a relatively shorter GD_a .

4.2. Comparison between MCF and GD_a

To better compare these results, we present the descriptive statistics of GD_a by grouping them into MCF categories (Table 1) and illustrate the variation of GD_a across MCF categories in a Box-Whisker Chart (Fig. 3). It visually shows that a large proportion of overlapped GD_a existing between single cropping and double cropping. In particular, the upper limit of GD_a of single cropping (214d) was just a few days less than that of double cropping (217d), and the lower limit of GD_a of double cropping (171d) was even lower than the 75% quartile of GD_a of single cropping (186d) (see the shadow area marked out in Fig. 3). It further shows that the GD_a for triple cropping is notably higher than the rest groups, suggesting that cropland use intensity is high for both measurements, hence no confusion exists in this case. Moreover, considering the share of triple cropping is very limited in the study region, we do not include the triple cropping case in the following analysis, which simplifies the subsequent statistical tests as well.

We carry out statistical tests to further explore the possible difference of GD_a between single cropping and double cropping. The prior Kolmogorov-Smirnov Normality Tests reject the null hypothesis, suggesting that GD_a are not normally distributed for all the MCF categories (Table 1). Therefore, we focus on the non-parametric tests first (e.g. median test, Mann-Whitney U test, and Moses Test of Extreme Reactions), and apply a parametric test as a supplement (i.e. analysis of variance, ANOVA). The null hypotheses (H_0) for the selected tests are listed in Table 2. The results show that the means, medians, and distribution of GD_a are significantly different between single cropping and double cropping. However, the range of GD_a is the same across MCF categories (Table 2). It shows that the GD_a between single cropping and double cropping, especially for the overlapped domain (Fig. 3), substantially causes confusion.

4.3. Integrated characterization of cropland use intensity

As we find that the 75% quartile of GD_a of single cropping (186d) was very close to the 25% quartile of GD of double cropping (187d), it indicates that the GD_a of single cropping at the upper quarter is likely to be substantially longer than the GD_a of double cropping at the lower quarter, even though single cropping represents a low-frequency intensity for cropland use comparing to that of double cropping. We then use these quartiles as the thresholds to determine the x-axis for the 2×2 quadrant matrix. Specifically, $GD_a \in [60, 186]$ are regarded as shorter growth duration, while $GD_a \in [187, 217]$ are regarded as longer growth duration.

Based on the 2×2 quadrant matrix, we combine the two maps in Fig. 2 to recharacterize cropland use intensity in an integrated manner (Fig. 4). The bivariate map shows that single cropping with shorter growth duration – representing a lower cropland use intensity – mainly concentrates in the northern part (blue, which accounts for ca. 44% of the total cropland area), and that double cropping with longer growth

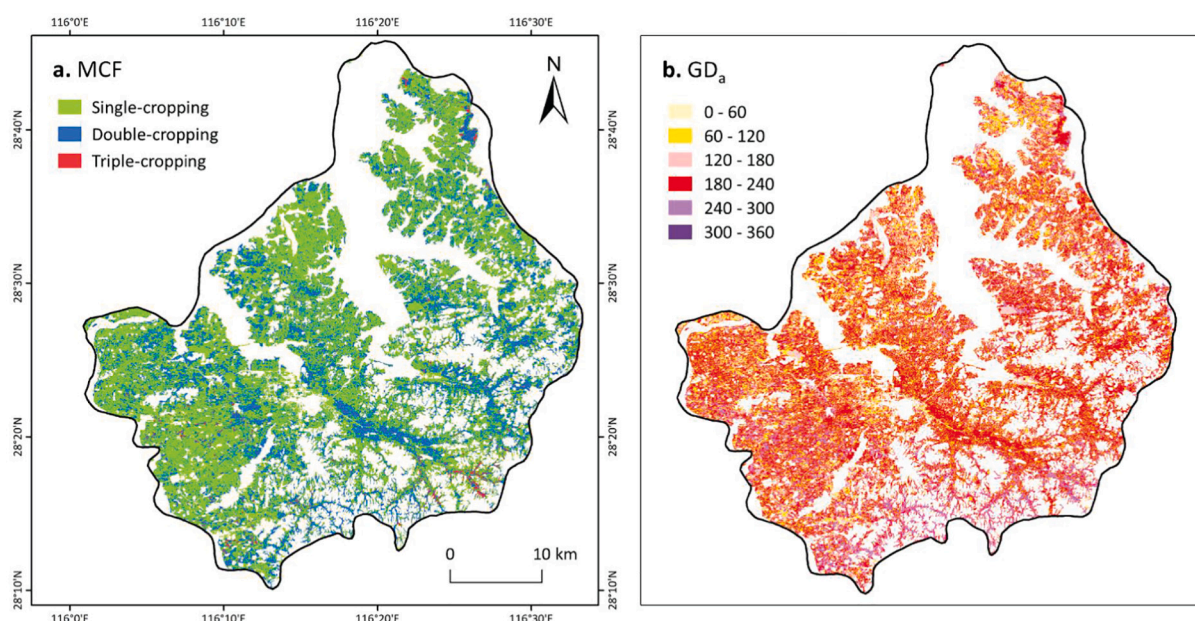


Fig. 2. The MCF map (left) and GD_a map (right) in Jinxian County, South China.

Table 1

Descriptive statistics of GD_a grouped by MCF categories.

	MCI = 1	MCI = 2	MCI = 3
Share	65%	34%	1%
Mean	146.29	193.56	289.00
Std. Deviation	39.450	8.661	1.477
Std. Error	0.025	0.008	0.006
Median	139	194	289
1% quartile	60	171	285
25% quartile	108	187	288
75% quartile	186	199	290
99% quartile	214	217	293
Skewness	0.193	0.134	-0.704
Kurtosis	-1.511	-0.255	0.850
Kolmogorov-Smirnov Tests of Normality ^{a,b}			
Statistic	0.140	0.032	0.226
df	2,443,794	1,176,069	63,375
p	0.000	0.000	0.000

Note: a. H_0 : GD_a are normally distributed within an MCF category; b. with Lilliefors Significance Correction.

All data is processed in IBM® SPSS® Statistics.

duration – representing a higher cropland use intensity – mainly locates at the central and southern part (yellow, which accounts for ca. 28% of the total cropland area). In the west part of the study region, the double-cropping areas are likely to have a shorter growth duration (green, which accounts for ca. 6% of the total cropland area) while the single cropping areas are likely to have a longer growth duration (red, which accounts for ca. 22% of the total cropland area).

5. Discussion

A lot of attention has been paid to measure cropland use intensity. Yet, the interpretations of land-use intensity are relatively less, which is mainly because the commonly shared definition and terminology are still lacking (Erb et al., 2013). Although the Food and Agriculture Organization of the United Nations (FAO) officially defines intensification as an increase in agricultural production per unit of inputs. It still frequently causes confusion and sometimes even creates contradicting understandings. For example, by using the multi-cropping index as a dependent variable, Jiang et al. (2013)'s analysis suggested that a

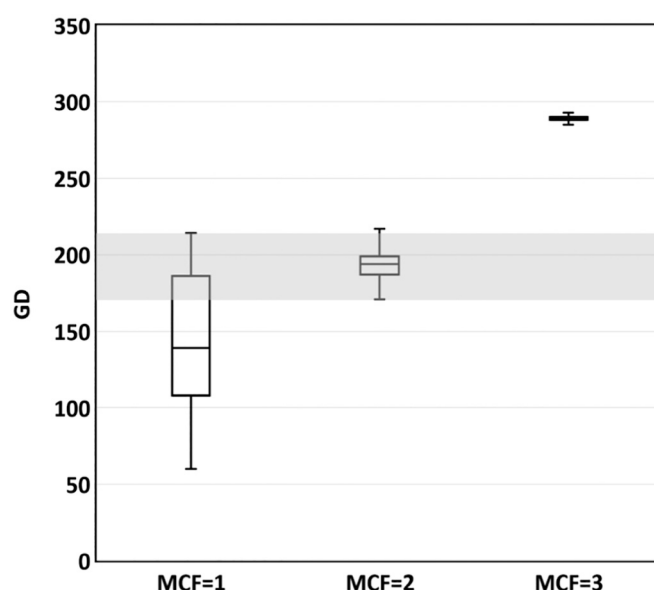


Fig. 3. A Box-Whisker Chart for comparing MCF and GD_a. The x-axis represents the frequency and the y-axis (Box and Whisker) represents the duration. The whiskers indicate the upper/lower limits of the GD_a range by excluding the 1% outliers, the edge of boxes indicate the 75% quartile and 25% quartile of the GD_a range respectively, and the lines within boxes indicate the median value of the GD_a range. The dark shade represents the domain of overlapped GD_a across MCF categories, which indicates that confusion might exist when using different indicators for measuring cropland use intensity.

declined cropland use intensity in China can be explained by the large-scale conversion from cropland to urban land. By contrast, Yu et al. (2019)'s analysis suggested that cropland use intensity has substantially increased in China because more food was produced with less cropland area. Nevertheless, Lassaletta et al. (2014) found that China's increased crop production was associated with a declined fertilizer use efficiency, hence suggesting an opposite trend against intensification according to FAO's definition.

These examples indicate that a higher cropland use intensity measured by one indicator is not necessarily interpreted as high by

Table 2

Statistical tests on the difference of GD_a between single cropping and double cropping.

Statistical test	h_0	P	Result
One-way ANOVA	The means of GD_a are the same across MCF categories	0.000 ^a	Reject
Median	The medians of GD_a are the same across MCF categories	0.000 ^a	Reject
Mann-Whitney U	The distribution of GD_a is the same across MCF categories	0.000 ^a	Reject
Moses Extreme Reactions	The range of GD_a is the same across MCF categories	1.000 ^b	Retain

All data is processed in IBM® SPSS® Statistics.

^a The significant level is 0.05.

^b Exact significance is displayed for this test.

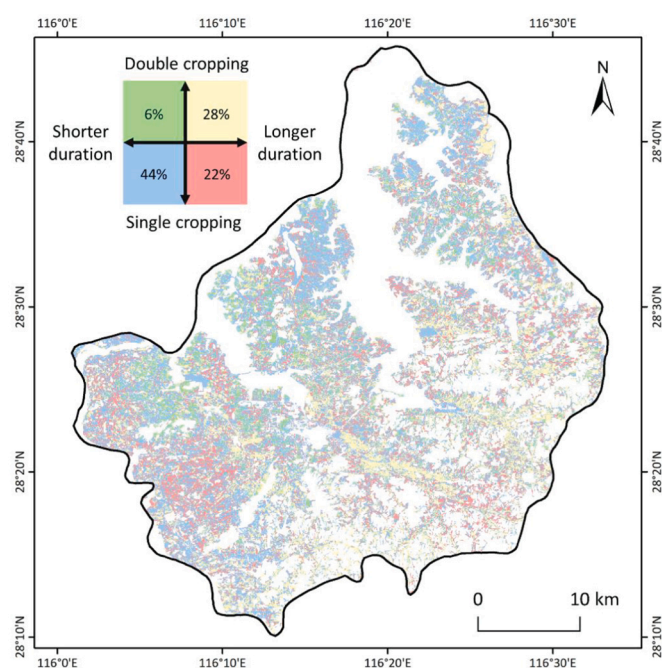


Fig. 4. A bivariate map of cropland use intensity by integrating MCF and GD_a . All values are rounded to the nearest integer.

another measurement, as confirmed in this study as well. The contradicting observations, e.g., in terms of MCF and GD, also suggest that cropland intensity may not be always measured as high for “both” indicators. This challenges the traditional assessments that cropland intensification can be achieved with the presence of a low cropland use intensity measured within a specific context. For example, to increase cropping intensity would improve the exploitation of the climate resource potential (Wu et al., 2018), to optimize crop distribution would increase food production and reduce water use (Davis et al., 2017), to diversify crop sequences might also be a solution to increase yields and resource use (Andrade et al., 2017). Our study provides evidence that adding another cropping cycle not only depends on the current cropping intensity but also relies on how many growing degree days are still available to sustain the other crop. A recent study by Barbieri et al. (2019) also found that intensification not only results in changes in agricultural inputs but also in changes in the types of crops grown. It implies that we cannot simply compare cropland use intensity across different indicators, as we all know that comparing apple to orange makes no sense. The bivariate map of the current study (Fig. 4) shows that more than one-quarter of the total croplands in the study area have displayed a contradicting intensity. In particular, the majority are single-cropping with a longer duration. As multiple-cropping usually requires

more intensive management and the yield per unit per season is lower than single-cropping (Wang et al., 2017), it suggests that selecting longer season crops to prolong growth duration is likely to be an easier way for cropland intensification. The various measurements of cropland intensity reflect the intrinsic multi-facets of cropland intensification; and we do not necessarily need to unify them or favor one over the other. Nonetheless, more efforts are required to understand the multidimensionality of the intensification process in the future, including the analysis of trade-offs, synergies and opportunity costs of cropland intensification strategies.

Cropland-use intensity is multi-faceted, yet in this paper, we merely focused on two indicators, i.e., multi-cropping frequency and crop growth duration. This has been elaborated that the selected indicators are very essential according to the definition of cropland use intensity, and they are closely related to each other. Moreover, they can be measured simultaneously from the remote sensing time series—which is also important for the consistent comparison analysis. As different measurements of cropland use intensity have been rarely compared, we have innovatively carried out a case study and provided evidence to the proposed hypothesis. In the current study, it is not our intention to assess which indicator is better between MCF and GD. Instead, we just simply compare them from an interdisciplinary point of view to raise awareness. Nevertheless, a continuous variable like GD might be able to explain more of observed variance e.g., in the annual net primary production, than simply documenting the MCF. The potential contribution of observing GD, comparing with other metrics, should be further quantified in future studies. Despite using a small study area to validate the two measures of intensity against empirical data seems sensible, we tried to provide a robust and replicable method that can be quickly applied in other places where multiple cropping is possible and is substantially existing. For such a pilot study, simplification should also be considered as it is difficult to include every aspect at the very beginning. We will add more indicators in the subsequent analysis to have a more comprehensive overview. Moreover, additional questions such as which determinants are behind these patterns and relationships, and how patterns change over time are important for better understanding cropland use intensity (Malek and Verburg, 2020; Yu et al., 2018), which have not been addressed in the current study, and are expected to be explored in subsequent analysis.

When using the time-series NDVI to measure MCF and GD on croplands, we tried to eliminate the background noises induced by different types of crops as they might have different duration and also growth habits and biomass production which also reflects in variable NDVI. Firstly, vegetables are not considered because their growth durations are generally shorter than 60 days in this region, and in some cases, the MCF of vegetable cultivation could be very high (Huong et al., 2013). We screened the GD lower than 60 days out to make the results clearer to explain. We focused on cereal crops and cash crops that have a relatively longer growth duration, including rice, maize, rapeseed, sesame, peanut, which are also the major crops in the study area (Xiang et al., 2019). Secondly, we consulted experts and asked farmers during the field survey regarding the local crop calendar and crop combination. The growth duration for summer crops is generally between April and September. The growth duration for winter crops is generally between October and April of next year. As a result, we detected and eliminated the “false peaks” if they are not accordant to the local crop calendar and crop combination. Thirdly, we resorted to literature to empirically set thresholds toward the smoothed NDVI curve. For example, all peak values should be no less than 0.35 (Liang et al., 2012). Moreover, the difference values between two adjacent peaks should be no less than 40% of the higher peak value, otherwise, the lower peak will be no longer regarded as a peak (Gao et al., 2015).

The various spatial datasets – depicting cropland area, crop distribution, cropping intensity, fertilizer input, irrigation extent – provide opportunities for the comprehensive assessments of cropland intensification at a large geographical scale (Kuemmerle et al., 2013). Yet, few of

these existing datasets are directly comparable due to the varied methods, data source, and spatial resolution applied during data production. For example, the MCF maps produced by remote sensing images only focused on cropping intensity while largely overlooking the crop types and their combination (Xiang et al., 2019; Yan et al., 2019); the Spatial Production Allocation Model disaggregates the crop statistics from census to grid yet without any information on cropping intensity and fallowed cropland (You et al., 2014; Yu et al., 2020). It is difficult to couple these datasets for the more comprehensive cropland intensification assessments at this moment. Whilst our study indicates the possibility to depict the characteristics of cropland use in a more integrated manner: we mapped the combined characteristics of MCF and GD_a by using the same data input and methodology. This research provides a valuable contribution in portraying the multidimensionality of intensification and the complexity of measuring intensification from various perspectives.

6. Conclusion

As cropland intensification is a critical strategy for achieving global food security, it is important to understand the multifaceted nature of the intensification process and the complexity of measurement of intensity. In this research, we demonstrate the possible inconsistency among intensification indicators. We hypothesize that a high cropland use intensity measured by one indicator is not necessarily interpreted as high by another measurement. Based on empirical knowledge and remote sensing imageries, we map the MCF and GD_a as two independent measurements at a high spatial resolution for cropland use intensity in Jinxian County, Southern China. We then relate these two indicators at the pixel level to test the hypothesis. We find a significant overlap of GD_a between single cropping and double cropping both visually and statistically, and that the GD_a of single cropping at the upper quarter is substantially longer than the GD_a of double cropping at the lower quarter. A bivariate map shows that 28% of the total cropland has displayed a contradicting intensity, most of which are single-cropping with a longer duration. As a result, our hypothesis has been confirmed that a high cropland use intensity measured by MCF is not necessarily interpreted as high by GD_a and vice versa. It implies that measuring and interpreting cropland use intensity is equally important and that more efforts are required to understand the multidimensionality of the process of cropland intensification. Different alternatives of intensification might have different consequences, at the same time, different measurements may convey contradicting messages for policymakers. Our study suggests that distinct policy measurements are required in specified contexts for pursuing the goal of sustainable agricultural intensification.

Declaration of Competing Interest

The authors declare that they have no conflict of interest.

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