Application of Convolutional Neural Networks in Detecting Cropping Intensity: An Attempt based on Global Typical Samples⋆

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Abstract. Accurate estimation of cropping intensity is crucial for agriculture production, land management, and food security. Traditional land surveys and remote sensing techniques are often constrained by time and space limitations, while deep learning, particularly Convolutional Neural Networks (CNN), offers new opportunities to address this challenge. In this paper, we explored the use of CNN for calculating cropping intensity. First, we collected multi-temporal satellite imagery, the Enhanced Vegetation Index (EVI) of MOD13Q1 as the database which spans various cropping growth stages. Subsequently, a CNN model was employed to learn features from these datasets to capture changes in crop growth. After training, the CNN model can identify and classify different cropping intensity, indicating the frequency and intensity of crop planting in different regions and periods. Our research findings suggest that CNN holds promise for cropping intensity estimation. It provides higher precision of cropping intensity of over 90%, enhancing the understanding of dynamic changes in cropland for decision-makers. Furthermore, CNN exhibits adaptability to diverse geographic environments and crop types, thereby enhancing its generalization capabilities. This approach holds significant implications for improved land management, agricultural production, and agricultural policy efficiency. By introducing deep learning techniques to crop planting intensity estimation, we offer novel tools and methods for sustainable agriculture and effective land management. Future research will further refine this approach to meet monitoring requirements in different regions and environmental conditions.

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1 Introduction

Food security has become an important research hotspot with the increasing total population worldwide [1]. Among the important factors affecting food production, cropland area and yield per unit area are the two most important factors that control the lifeblood of food security [2, 3]. Cropping intensity is a critical metric that measures the frequency and density of crops cultivated in a specific area, which is a significant indicator used to measure multi-cropping systems utilization of cropland resources [4]. The cropping intensity can not only be used as a basis for estimating grain yield per unit area but also as a key parameter for evaluating the intensity of cropland use, agro-ecological system simulation, etc., which is of great significance [5]. Systematic study of cropping Intensity could provide data support for future high-quality cropland development and food security, and provide a scientific basis for the assessment of the United Nations Sustainable Development Goals (SDGs) and the management and potential planning of cropland at a global scale [6]. Accurate estimation of cropping intensity is essential for agricultural production, land management, and food security [7].

Time-series remote sensing data can better describe the growth process of crops, which is the theoretical basis for monitoring the cropping intensity using remote sensing technology [8, 9]. Numerous researchers have developed global or regional cropping intensity maps using remote sensing datasets or statistical datasets [10, 11]. However, traditional survey and monitoring methods are often constrained by time and cost, necessitating faster, more efficient, and more accurate approaches to estimate cropping intensity [12]. In recent years, the rapid advancements in remote sensing, big data, cloud computing, computers, sensors, and other technologies and hardware have ushered in a new era of cropping intensity monitoring [13, 14]. These developments have not only provided us with an abundance of new data but have also introduced innovative methods for monitoring cropping intensity [15].

Recently, deep learning techniques, particularly Convolutional Neural Networks (CNN), have made significant advances in image analysis and remote sensing [16-18]. CNNs possess outstanding feature extraction and pattern recognition capabilities, making them an ideal choice for processing remote sensing imagery [19-21]. Leveraging CNNs, we can extract rich information from satellite images to more accurately estimate cropping intensity.

This study aims to explore how CNN technology can be employed to estimate cropping intensity. We collected multi-temporal satellite imagery covering different seasons and growth stages of cropland, using the Enhanced Vegetation Index (EVI) data of MOD13Q1 to build the database. These images provide the whole phenological process for capturing the dynamic changes in crop cultivation. Through CNN models, we can automatically extract and analyze features from the time-series database to estimate the cropping intensity for cropland.

The results of this study have wide-ranging applications. It contributes to improving the efficiency of land monitoring, land planning, and agricultural decision-making, providing more information for agricultural production to meet the growing global food demand. Additionally, this approach serves as a paradigm for the application of deep learning technology in remote sensing and agriculture, inspiring further research and innovation.

By introducing deep learning to estimate cropping intensity, we offer new tools and methods for land management and agricultural production, with the potential to positively impact sustainable agriculture and food security [22]. This research aims to better understand and utilize land resources, providing support to rural communities and the global food supply chain [23].

2 Related Works

Remote sensing monitoring for cropland has emerged as a crucial tool in modern agriculture, enabling efficient and accurate assessment of cropping intensity, growth conditions and land use patterns. This field of study combines the power of remote sensing technologies with advanced data analysis techniques to monitor and analyze cropland dynamics on a large scale. In recent years, there has been a growing interest in utilizing CNN for cropland monitoring, leveraging the capabilities of deep learning algorithms to extract meaningful information from remote sensing imagery. However, few papers apply the estimation of cropping intensity using deep learning techniques, which has gained significant attention due to its Strong learning and training capability [24]. This section provides an overview of the related works in these three key areas, highlighting the advancements, challenges, and potential future directions in the field.

2.1 Remote Sensing Monitoring for Cropland

Remote sensing monitoring tools based on cropland mainly utilize traditional image processing algorithms, feature extraction algorithms and machine learning methods [25-27]. These methods help agricultural professionals to extract useful information from remotely sensed images for monitoring the condition of cropland and for crop classification, estimation and prediction [28, 29].

Traditional image processing algorithms play an important role in remote sensing monitoring of cropland [30-32]. These algorithms perform preprocessing of remotely sensed images, including denoising, enhancement and image alignment [33]. In addition, traditional image processing algorithms can be applied to tasks such as image segmentation, target detection, and image alignment to extract crop information from farmland images, which are important traditional monitoring tools [34, 35].

Feature extraction algorithms are another important tool in remote sensing monitoring of cropland, which are mainly used to extract useful features from spatio-temporal remote sensing images of cropland. These features can include texture, shape, time series and spatial distribution of crops. By extracting these features, the type, area, cropping intensity, yield, etc. of cropland can be directly estimated and predicted [30, 36].

Machine learning methods also play an important role in remote sensing monitoring of cropland. These methods can utilize existing remote sensing image data and corresponding labeling information to achieve crop classification and estimation by training models. Commonly used machine learning methods include support vector machine, great likelihood, decision tree, and random forest [37-39]. These methods can learn the patterns and laws in farmland images based on existing data and be used for the analysis and prediction of new remote sensing image data.

In summary, the commonly used tools in remote sensing monitoring of cropland can help to extract useful information from remotely sensed images, realize the classification, estimation and prediction of crops, and provide decision support for agricultural production.

2.2 Application of CNN for Cropland Remote Sensing Monitoring

Convolutional Neural Networks (CNN), as an exceptional deep learning model in the realm of computer vision, have found extensive application in remote sensing. In recent years, CNNs have made remarkable progress in this field [40-42].

One of the most prevalent applications is CNN's outstanding performance in remote sensing image classification tasks. By leveraging the convolution and pooling operations of CNN, spatial and spectral features can be efficiently extracted from remote sensing images, enabling high-precision classification. For instance, through training a deep CNN model, remote sensing images can be categorized into different feature classes such as buildings, roads, and vegetation [43, 44]. This capability is crucial for applications like urban planning, environmental monitoring, and resource management [45].

Furthermore, CNN has achieved remarkable results in remote sensing image segmentation tasks. Remote sensing image segmentation involves assigning each pixel in an image to its corresponding category, which is vital for applications such as land use, disaster monitoring, and agriculture[18]. CNN's convolution and deconvolution operations enable accurate segmentation of remote sensing images [16, 17]. For example, CNN models can accurately segment targets like buildings, water bodies, and roads in remote sensing images, providing valuable information for urban planning and environmental management.

Additionally, CNN has found wide application in tasks such as super-resolution reconstruction of remote sensing images, target detection, and change detection [26, 46]. By harnessing CNN's feature extraction and learning capabilities, the spatial resolution of remote sensing images can be enhanced, resulting in clearer images [47]. Moreover, CNN can detect target objects in remote sensing images, such as vehicles, ships, and buildings, supporting traffic monitoring and security efforts [48, 49]. CNN is also capable of detecting changes in remote sensing images, such as land use changes and post-disaster alterations, providing crucial information for resource management and disaster monitoring [50, 51].

The application of CNN in remote sensing holds immense potential. By utilizing CNN's powerful feature extraction and learning capabilities, tasks such as classification, segmentation, super-resolution reconstruction, target detection, and change detection of remote sensing images can be accomplished, offering significant support for earth observation and environmental management [52]. Compared to traditional remote sensing methods, CNN exhibits higher accuracy and robustness in this field, making it widely adopted for remote sensing monitoring and analysis.

2.3 Estimation of cropping intensity based on deep learning

Compared to conventional methods for analyzing remote sensing images, deep learning techniques have demonstrated superior capabilities in model generalization and have achieved higher prediction accuracy in agricultural high-resolution remote sensing image analysis [53]. While significant progress has been made in remote sensing classification and other areas, calculating the multiple cropping index of cropland remains a challenge.

Although previous studies have introduced methodological innovations for cropping intensity, traditional approaches still dominate the field. To date, there is no deep learning algorithm specifically designed for cropping intensity. This limitation is partly due to the constraints of available datasets and the challenges associated with global generalization, which greatly hinder the development and application of cropping intensity analysis.

Therefore, it is crucial to develop a deep learning algorithm that can be applied globally to efficiently calculate cropping intensity, addressing this important challenge.

3 Datasets and Methods

3.1 Datasets

The vegetation index is commonly used to describe crop growth conditions, such as the Normalized Difference Vegetation Index (NDVI) [54], and Enhanced Vegetation Index (EVI) [55]. In this paper, we used the time series curve of EVI for estimating cropping intensity (see Fig.1). Usually, EVI is more sensitive to high biomass areas, less affected by atmospheric and soil interference, and more capable of highlighting vegetation information [56, 57]. The vegetation index dataset from the MODIS Terra satellite is generated every 8 or 16 days, with spatial resolutions of 250 meters, 500 meters, and 1000 meters, with 250 meters being considered the optimal resolution for monitoring crops [58, 59]. The EVI was obtained from the NASA Earth Observing System Data and Information System (EOSDIS) Land Processes Distributed Active Archive Center (LP DAAC). The study period covered the years from 2000 to 2020, allowing for a comprehensive analysis of cropping intensity over two decades.

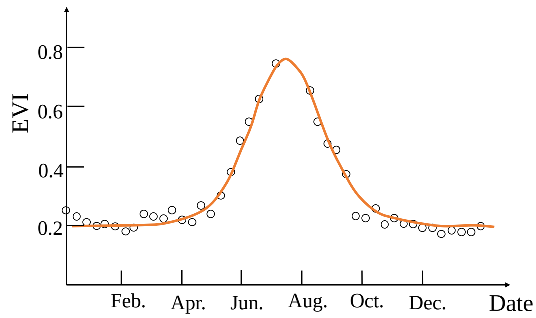

Fig. 1. An example of an EVI time series and the fitted curve for one year.

In this study, the MODIS product MOD13Q1 was used, which provides EVI time series with a spatial resolution of 250 meters every 16 days, as the primary data for calculating the global cropping intensity. MOD13Q1 generates composite vegetation indices for 16 days using the combined 8-day surface reflectance data (MOD09A1) from Terra and Aqua. And the calculation formula for EVI is as follows:

$$\mathrm{EVI} = 2.5 \times \frac{\rho_{\mathrm{NIR}} - \rho_{\mathrm{Red}}}{\rho_{\mathrm{NIR}} + 6 \times \rho_{\mathrm{Red}} - 7.5 \times \rho_{\mathrm{Blue}} + 1} \quad (1)$$

In the equation, ρ_{NIR}, ρ_{Red}, and ρ_{Blue} represent the reflectivity of the near-infrared band, the red band, and the blue band, respectively.

3.2 Samples

This study introduced verification sample points—2492 samples, which were verified year by year during 2001 to 2019 from our previous research[60]. These samples are extracted based on qualified cropland types in FROM-GLC datasets [37, 61]. Each sample point underwent rigorous manual interpretation by multiple individuals, considering both the MODIS EVI time series curves and the geographic coordinates, to assess its annual cropping intensity: 0, 1, 2, or 3. Each sample point was interpreted year by year from 2001 to 2019, and the resulting sample points are presented in the following figure (see Fig.2).

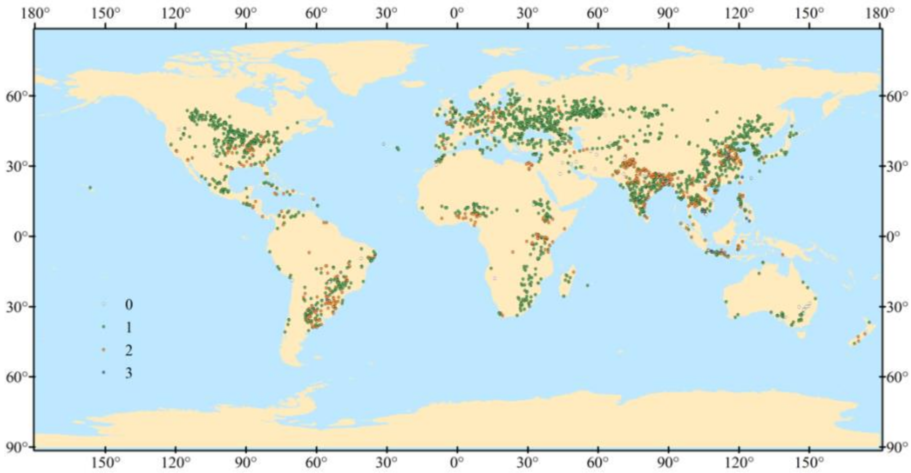

Fig. 2. Sample distribution of global cropping intensity (the illustration is an example of the cropping intensity for 2019).

The cropping intensity values include 0, 1, 2, and 3, representing no planting, single-season planting, double-season planting, and triple-season planting, respectively. The dataset does not encompass Greenland and Antarctica, as these two continents do not have the distribution of cropland [62].

3.3 CNN

We employed a Convolutional Neural Network (CNN) architecture tailored for cropping intensity estimation. CNNs are renowned for their ability to automatically extract relevant features from complex data, making them a robust choice for the intricate task of cropping intensity estimation [63]. The CNN usually comprises multiple convolutional layers followed by max-pooling layers for feature extraction and spatial downsampling. A series of fully connected layers and a final softmax layer are used for classification [64]. The major operations in the CNN could be described as the equation 2:

$$O_l = \sigma(\sum_i (W_i * I_{l-1}) + b_l) \tag{2}$$

Where: O_l is the output feature map of the l-th layer. I_{l-1} is the input feature map of the previous layer. W_i represents the convolutional kernel parameters. b_l is the bias for the l-th layer. $\sigma(.)$ is an activation function applied element-wise.

The CNN uses a convolution operation to extract relevant features from the input data. It involves a convolutional kernel (a small filter) moving over the input image or feature map, performing element-wise multiplications and summing the results. An activation function applied after the convolution, introduces non-linearity to the model. It helps the network learn complex patterns and relationships in the data. A commonly used activation function $\sigma(.)$ is the Rectified Linear Unit (ReLU). Pooling is applied to reduce the spatial dimensions of the feature maps and retain important information.

Max-pooling is a common technique where, within a defined window, the maximum value is selected. After feature extraction and spatial reduction, fully connected layers are used to perform classification or regression tasks. These layers connect all neurons from the previous layer to each neuron in the current layer. These operations collectively allow the CNN to automatically learn hierarchical features from input data, making it effective in tasks like cropping intensity estimation.

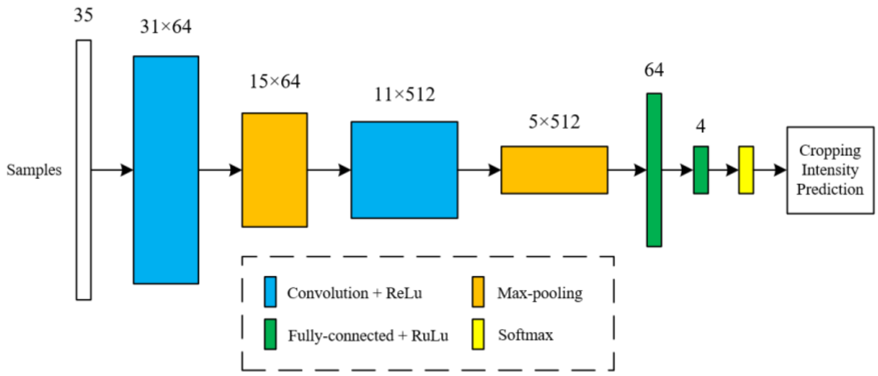

Fig. 3. Structure of CNN (mainly composed of two convolutional networks and two fully connected networks).

The fully trained CNN is usually more flexible and expandable for architecture and parameters [65]. A relatively simple CNN was applied to cropping intensity estimation. Fully trained CNN was used in this study on long time series datasets as input and output a predicted cropping intensity label. The network consisted of two convolutional layers (Conv1 and Conv2) followed by two fully connected layers (FC1 and FC2) (see Fig.3). Conv1, with a single input channel, generates 64 output channels using 5*5 convolution kernels and ReLU activation. A 2*2 max-pooling layer reduces spatial dimensions. Conv2 builds on Conv1's 64 output channels and expands to 512 output channels, employing 5*5 convolution kernels with ReLU activation and additional 2 x 2 max-pooling. The fully connected layers, FC1 and FC2, further process the extracted features. FC1, with 2560 input nodes, reduces dimensionality to 64 nodes, while FC2 maps these 64 nodes to 4 output nodes, representing crop planting intensity classes.

This CNN configuration, coupled with the Lion optimizer, is tailored to effectively extract features from time series datasets and predict crop planting intensity accurately, contributing to the overall success of our crop analysis framework [66]. During the training process, we employ a categorical cross-entropy loss function to guide and refine the model's parameters. The Lion optimizer dynamically adjusts learning rates based on parameter gradients, initiating the process with an initial learning rate of 0.000098.

3.4 Accuracy Assessment

To assess the accuracy of our year-by-year multiple cropping index results within cropland, we performed a comprehensive evaluation using established metrics and techniques. The accuracy assessment involved the use of a confusion matrix, a fundamental tool in classification performance evaluation.

The confusion matrix provided us with the counts of true positive (TP), true negative (TN), false positive (FP), and false negative (FN) instances, enabling us to calculate key indicators that quantify the model's performance. These indicators are crucial for understanding the reliability and precision of our methodology. Using the confusion matrix, we introduced Overall Accuracy (OA), Producer Accuracy (PA) and Producer Accuracy (PA) as the accuracy assessment.

Overall Accuracy, a pivotal metric, gauges the percentage of correctly classified samples out of the total number of samples. It provides a global assessment of our model's performance and is calculated as:

$$\mathrm{OA} = \frac{TP+TN}{TP+TN+FP+FN} \tag{3}$$

Producer Accuracy, also known as Sensitivity or True Positive Rate, measures the model's ability to correctly classify positive instances (crop planting) within the positive class. It is computed as:

$$\mathrm{PA} = \frac{TP}{TP+FN} \tag{4}$$

User Accuracy, an indicator of precision, evaluates the accuracy of positive predictions made by the model. It is calculated as:

$$\mathrm{UA} = \frac{TP}{TP+FP} \tag{5}$$

These quantitative assessments, facilitated by the confusion matrix and these key metrics, provide valuable insights into the overall accuracy, sensitivity, and precision of our methodology. The results of this accuracy assessment are pivotal in determining the reliability and suitability of our approach for crop analysis and monitoring within cropland.

4 Results and Analysis

4.1 Experiments on CNN

We extended the EVI time series for each year from 2001 to 2019 using data from the EVI period spanning from 2000 to 2020. This extension involved including the data from the three months at the end of the previous year and the three months at the beginning of the next year, resulting in a total of 18 months in each annual EVI time series. Considering that we utilized the 16-day MODIS EVI product, resulting in 23 sets of data each year, the extension expanded the dataset for annual cropping intensity estimation by an additional 6 data points before and after, totaling 35 sets of data.

Adhering to the organizational data input guidelines, we conducted data cleaning before feeding the data into the CNN. In cases where the 35 sets of data of EVI time series data used for each year's training were incomplete, or the verification indicated missing cropping intensity results, such data was excluded from input into the CNN network for training. After preprocessing, a total of 44,794 valid data points were obtained. Each data point is segmented into data and label components, with the data dimension being <1, 35> and the label values ranging from <0, 1, 2, 3>. Following a 4:1 ratio, the data was randomly split into training and test sets. During both of the training and testing phases, a batch size of 1000 was utilized, and hyperparameters were fine-tuned as needed to achieve the best performance.

4.2 Cropping Intensity Results

By analyzing the confusion matrix and quantitative indicators, this study conducted an accuracy assessment of the annual multiple cropping index results within the cropland (refer to Table 1). The findings reveal that the cropping intensity estimation developed in this study for the period 2001 to 2019 demonstrates a high level of overall accuracy. The average overall accuracy (OA) across all years is 90.89%, with a peak value of 91.87% observed in 2011. Notably, the accuracy of single cropping intensity estimation surpasses that of multiple cropping intensity estimation.

When examining the user's accuracy (UA) and producer's accuracy (PA), it becomes evident that misclassification errors are more prevalent in single cropping intensity estimation compared to omission errors (UA < PA). This suggests a higher likelihood of overestimation in single cropping intensity estimation. Conversely, for multiple cropping intensity estimation, the occurrence of misclassification errors is lower than that of omission errors, indicating a tendency towards underestimation (PA < UA). This discrepancy can be attributed to the limited sample size and distribution proportion of multiple cropping intensity in this study, which adversely affects the accuracy of multiple planting estimations, particularly in terms of the differences between PA and UA.

Table 1. Global annual cropping intensity accuracy assessment from 2001 to 2019.

Year	UA（%）			PA（%）			OA (%)
	1	2	3	1	2	3	
2001	91.57	80.58	84.21	95.60	76.13	50.00	89.09
2002	91.50	84.76	87.50	96.59	77.60	63.64	90.12
2003	93.08	82.25	90.48	96.17	80.57	54.29	90.79
2004	93.95	83.40	88.46	96.55	83.05	63.89	91.71
2005	93.82	83.51	76.92	96.12	83.15	74.07	91.40
2006	91.98	82.55	72.73	95.30	77.52	72.73	89.52
2007	92.92	85.87	76.67	96.64	79.88	76.67	91.37
2008	93.73	82.47	75.76	95.89	84.25	71.43	91.05

2009	93.83	82.90	86.96	95.87	82.57	62.50	91.32
2010	93.93	83.81	83.78	96.01	82.96	72.09	91.60
2011	94.30	84.09	79.41	96.61	81.40	65.85	91.87
2012	92.57	80.34	86.11	94.98	81.57	62.00	89.69
2013	93.12	84.01	92.50	96.47	81.53	75.51	91.21
2014	93.47	84.57	75.61	95.99	81.62	77.50	91.18
2015	93.76	83.75	85.19	95.83	83.27	76.67	91.44
2016	93.13	86.59	79.31	97.04	82.08	65.71	91.60
2017	91.80	84.21	75.61	96.19	77.98	72.09	89.90
2018	92.44	84.41	79.55	95.69	82.49	79.55	90.39
2019	93.50	86.49	77.14	96.48	81.75	79.41	91.73

4.3 Comparison with Other Products

To further evaluate the accuracy of the multiple cropping Intensity estimations, this study introduced the Global Cropping Intensity (GCI) dataset[60], which utilizes traditional methods based on MODIS data, for comparison. By analyzing the global sample of Chapter 3.2, we extracted the GCI data year by year from 2001 to 2019. The overall accuracy (OA) of the global cropland multiple cropping intensity estimated by this study using CNN is depicted in the following figure (see Fig.4).

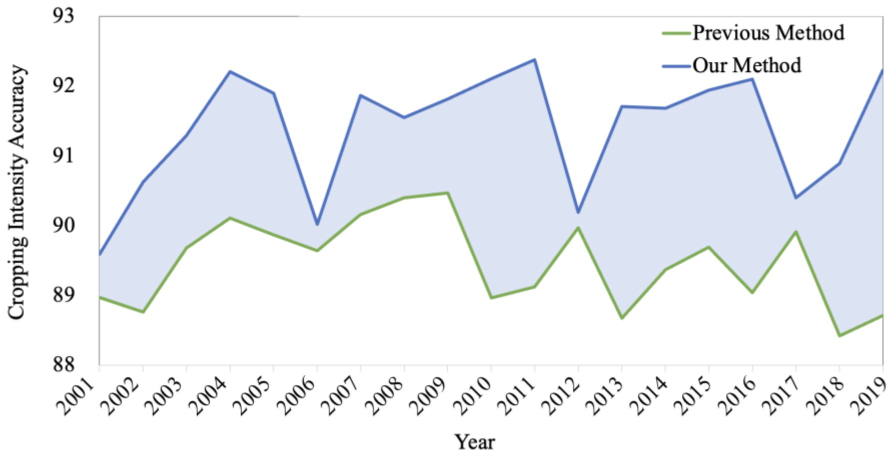

Fig. 4. The overall accuracies of our method and previous method from 2001 to 2019.

As depicted in the figure, both the previous method and our method exhibit satisfactory overall accuracy for the global cropland multiple cropping intensity, with OA exceeding 85% in both cases. Furthermore, the OA accuracy of GCI ranges from

87.92% (2018) to 89.97% (2009), while the OA accuracy of MCN ranges from 89.09% (2001) to 91.87% (2011). These results demonstrate that our study achieves improved accuracy in mapping the global multiple cropping intensity using CNN. Specifically, compared to the GCI dataset, our method shows an OA improvement of nearly 2%, further validating the reliability of this study and establishing a solid foundation for future utilization of deep learning in generating global datasets.

5 Conclusion

Our study has yielded remarkable results through the comprehensive utilization of convolutional neural networks (CNN) for estimating the global multiple cropping intensity. By comparing it with traditional methods, our approach has achieved an improvement in the accuracy of estimating the global multiple cropping intensity. Traditional methods are often constrained by limitations in data processing and feature extraction when estimating the multiple cropping intensity. In contrast, CNN has the ability to automatically learn and extract image features, enabling it to better capture the spatial distribution and variations. Leveraging global generalized training samples and the advantages of deep learning, our CNN model provides more accurate predictions of the multiple cropping intensity for global cropland. This study demonstrates that CNN exhibits high precision and reliability in mapping the global multiple cropping intensity.

The findings of this study hold significant implications for global agricultural management and decision-making. Accurate estimation of the global multiple cropping intensity can enhance our understanding of cropland utilization and crop planting patterns, thereby optimizing the allocation of agricultural resources and facilitating crop yield forecasting. Moreover, this research provides robust support for future endeavors in generating global datasets using deep learning, establishing a solid foundation for further research and applications.

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