Incorporating Phenological Patterns and Multi-source Remote Sensing Images for Cropland Change Detection

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ABSTRACT:

Accurate information on cropland changes is critical for monitoring arable land minimum, ensuring national food security, and grasping the situation of agricultural production and supply. The change detection using remote sensing images is one of the main methods for quickly extracting cropland changes. However, existing methods were highly susceptible to seasonal differences due to the high heterogeneity of cultivated land. In this study, an integrated framework was proposed to perform change detection by incorporating phenological patterns and multi-source remote sensing images.There were two improvements in this proposed cropland change detection method: 1) the multi-source remote sensing images were utilized to fill the missing data within a time-series image stack by considering phenological patterns of cropland and 2) the Seq2Seq model considering phenological patterns was developed to extract changes in cropland directly. Compared to the traditional change detection methods, the proposed strategy was able to detect change process. Experiments demonstrated that the proposed method can significantly improved change detection accuracies, given a limited number of labeled samples.

1. Introduction

Cropland is the basic resource and condition of human existence, and its quantity and quality are an important basis for ensuring global food production security. Cropland areas are also among the main driving factors of global environmental changes, which can have wide-ranging and far-reaching impacts on biogeochemical cycles, hydro geochemistry, global warming, ecosystem function, and human health (Gomez et al. 2016). However, worldwide cropland changes have occurred during the past decades due to urban expansion, land desertification, and reforestation. Therefore, timely, accurate, and cost-effective cropland change detection is critical for agricultural and environmental sustainability,greenhouse gas emissions, effective policy management, and decision-making

Remote sensing has been widely used for measuring the spatial distribution and change analysis of large-scale cropland due to its advantages of macroscopic, efficient, and convenient(Tewkesbury et al., 2015; Hussain et al.,2013; Kumar et al., 2021). In the past few decades, scholars both domestically and internationally have proposed various change detection methods, such as direct comparison method, change vector analysis method, and post classification comparison method (Lu et al., 2016; Song et al., 2016; Gong et al., 2015). However, these traditional methods were highly susceptible to random interference factors and seasonal differences, resulting in pseudo changes in cropland. These pseudo changes include changes in the growth status of cropland, changes in coverage, and other internal characteristic structure changes. The monitoring of dynamic changes in cropland has become possible due to the accumulation of massive historical remote sensing data. In recent years, time series change detection methods such as disturbance anomaly detection and continuous change detection have been proposed one after another (Kennedy, et al.,2010; Amitrano et al., 2021; Kulkarni et al.,2020). Although these methods have achieved good change detection results in specific research areas, their detection accuracy and efficiency were greatly limited when it comes to detecting changes in farmland use at the large scale and land parcel level. The main reason was that the characteristics of cropland in remote sensing images are highly heterogeneous in space and highly dynamic in time. Furthermore, currently these methods only utilized spectral spatio-temporal features and did not take into account the characteristics of the cropland itself. Therefore, pseudo changes in cropland still existed, especially in mountainous or hilly areas with high heterogeneity and fragmentation.

In fact, there is rich phenological information hidden in the time series images of cropland. In the temporal space, the phenology of cropland shows a trend of single or multiple peaks distribution within the year (short-term) and periodic changes between years (long-term). The phenological characteristics of cropland can provided rich prior knowledge for eliminating pseudo changes (Pan et al., 2015; Xiao et al., 2009). However, high spatio-temporal remote sensing datasets are a necessary foundation for finely constructing the phenological trajectory of cultivated land. A single (optical) data source was highly susceptible to the influence of clouds and rainy weather, resulting in the absence of satellite coverage during critical periods of crop detection. Fortunately, with the rapid development of aerospace technology, remote sensing data of different spatial and temporal resolutions are experiencing explosive growth. These massive, multi-source remote sensing data not only enable continuous observation of the same area, but also provide detailed records of the spatio-temporal dynamic changes of various land features on the surface (Gim et al., 2020; Wulder et al., 2019; Gao et al., 2021; Gao et al., 2020). Meanwile, deep learning has shown its advantages in feature extraction and image classification, it can auto matically learn robust representations which could be helpful for change type identification (Gong et al., 2015; Kumar et al.,2021). The end-to-end structure of deep learning networks allows us to directly obtain change detection results from multi-source remote sensing images without setting change thresholds. In particular, the Sequence to Sequence (Seq2Seq) have great potential in detecting cropland changes and can handle input and output sequences of any length.

However, existing deep learning network models typically labeled different changes as discrete change categories, such as cropland becoming built-up areas or water bodies. Then, there will be different growth states within a time series cycle, and the cropland states at different time nodes are mutually influential. The corresponding output should be a sequence that can represent the changes in the cropland state. For example, during the process of transforming cropland into built-up areas, there will be a bare land state (cultivated land → bare land → built-up areas). How to directly extract this state change from remote sensing image time series will be of great significance for fine-grained dynamic monitoring of cropland.

In this letter, we proposed an integrated strategy to identify cropland changes, regardless of the impact of variations caused by crop phenologies. Specifically, in order to filled the observation gaps for time-series data sets, multi-source remote sensing images were introduced to capture the phenology formulation and estimates the missing values. Then, a cropland change detection sequence to sequence model (CropS2S) was proposed to generate change area according to change types. And, lastly, the enriched training samples can be used to feed the CropS2S for change process identification.

The innovation of this paper includes the following three aspects. Firstly, due to the different imaging mechanisms and signal expressions, there were significant differences in the response positions, amplitude sizes, and temporal trajectories of similar ground objects in multi-source data on temporal signals, making it difficult to achieve deep coupling of time series to time series. This article used deep convolutional transformation networks to construct multi-source temporal signal mapping relationships, fully considering spatio-temporal contextual information, and mining the correspondence between multi-source "sequence to sequence" to achieve the construction of high spatio-temporal dense datasets.

Secondly, the time series images of cropland contained rich phenological information, which was the temporal feature that distinguishes cropland from other land types. The Seq2Seq model lacked attention to phenological features. In order to highlight the difference between changing and invariant features, attention mechanisms were introduced to increase the weight of phenological features. On this basis, constructed a "sequence to sequence" Seq2Seq model can effectively avoid the occurrence of pseudo changes.

Finally, the pixels of changes in cropland types were very limited, and cropland types were particularly complex, making it difficult to select an ideal and sufficient number of change sequence samples through visual interpretation. This article expanded the training samples by truncating and recombining the sequence of cropland changes and generating adversarial networks. Meanwhile, unlike other change detection methods, this sequence model can outputed the dynamic change process of cropland within a certain time period, that is, the final output represented the dynamic change information of cropland within a certain time period.

The remainder of this paper was organized as follows. Section 2 introduceed the representation learning of cropland phenological and the CropS2S model in detail. Section 3 summarized the experimental results. Finally, the conclusion was detailed in Section 4.

2. Methodology

The basic idea of the change detection was based on time-series trend analysis to identify changes in spectral-temporal space. The framework of this approach was shown in Figure 1. First, change indicators time series were extracted from SAR image and Operational Land Imager (OLI) time series. Second, we applied the multi harmonic model to describe the tendency and temporal patterns of cropland over time because the second harmonics was sensitive to seasonal variability and intra-annual change. Then, CropS2S were established as the difference image, and change areas were detected using trained models, as detailed in Sections 2.1–2.2.

Firstly, based on the characteristics of high spatial heterogeneity and temporal dynamics of cultivated land, this project used principal component analysis to extract the optimal index sequence. Then, deep transformation networks were used to couple multi-source temporal data to form a high spatiotemporal density temporal dataset, minied temporal context information, and generated fine cropland phenological trajectories based on a multi harmonic model. Then, based on the aforementioned phenological trajectories, the attention mechanism was used to embed phenological features and complete the design and construction of the Seq2Seq model. Meanwhile, the network model loss function for phenological characteristics was optimized. Finally, to address the issue of sparse change samples in automatic extraction of change information, truncated amplification was used to construct change sequences, and adversarial networks were generated for sample amplification. Then, based on the constructed network model, extract information on changes in cropland. The input of the model was the change sequence in the phenological trajectory, and the output was a sequence of cropland change states with a length of T, such as the process of cropland → built-up area change. The size of the T value was related to the time span of the input sequence, the number of images included, and the cropland target. Determining the appropriate length of the output sequence was crucial for extracting information on cultivated land changes.

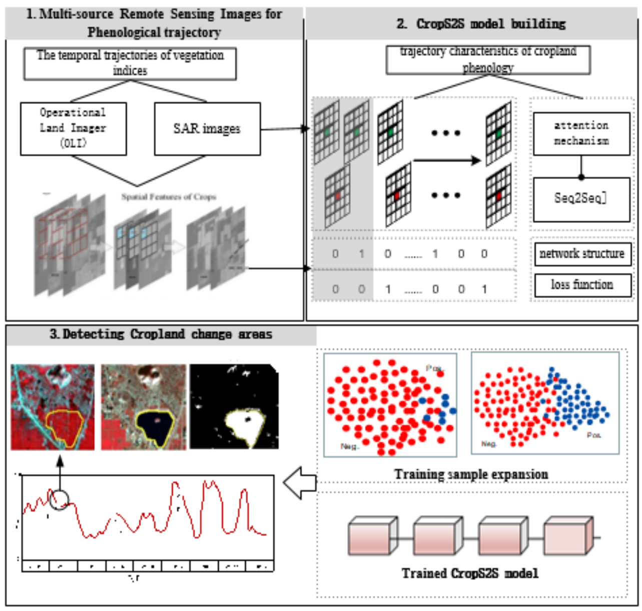

Figure 1. Flowchart of the proposed method.

2.1 Multi-source Remote Sensing Images For Phenological Trajectory

The temporal trajectories of vegetation indices (VI), such as the normalized difference vegetation index (NDVI), enhanced vegetation index (EVI), and land surface water index (LSWI), are of great significance in identifying vegetation changes or phenological monitoring. NDVI time series can accurately reflect the changes of seasonal characteristics and human activities and is considered to be an effective index to capture information changes of vegetation phenology. Therefore, we defined ‘phenological trajectory’ as the fitted curve through the NDVI time series of one year.

Multi-temporal remote sensing imagery has been regarded as an effective tool to monitor phenological trajectory. But optical sensors often missed key stages for crop growth because of clouds, which poses challenges to many studies. The synergistic of SAR and optical data was expected to lift this problem, especially in areas with persistent cloud cover. However, due to the different characteristics of optical and SAR sensors, it is difficult to build a relationship between the two with most existing methods, let alone construct the long-time correlations to fill optic observation gaps using SAR data. Inspired by deep learning, this study presents a novel strategy to learn the relationship between optical and SAR time series based on the sequence of contextual information. To be specific, we extended the conventional RNN to build Multi-CNN-Sequence to Sequence model, and formulate the correlation between the optic and SAR time series sequences. Therefore, high spatiotemporal datasets were obtained through deep convolutional network models. The method as shows in Fig.2.

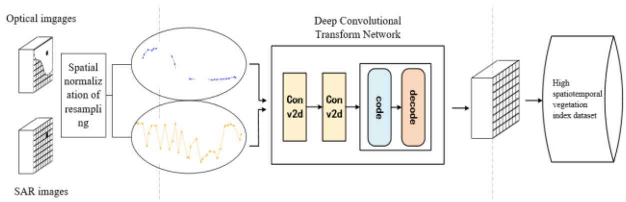

Figure 2.Multi-source Remote Sensing Images for Phenological trajectory

Then, to better represent the intraannual change patterns of cropland, the NDVI with higher sensitivity on dense vegetation was utilized to trace time-series signals. Numerous models have been applied to fill time series for land cover change analysis, such as the Gaussian and logistic function. However, Gaussian and logistic are unable to accurately fill different waveforms and capture growing season variations since they are always adapted to the upper envelope of the time series. Actually, cropland always owns a more complex phenology cycle, such as double- or triple-crop patterns within a year. Therefore, the harmonic model was more suitable to capture abrupt changes that occurred within a year. To fit vegetation index time-series x_i,i ∈ (1,... t) and retrieve cyclic phenological dynamics, we have the following formulation:

$$x_i = \mu + R\cos(f t + d) + e_t \tag{1}$$

where μ was the mean of the time-series, R was the amplitude of variation. f was the frequency of periodic variation, d was the phase or horizontal offset, t mean the time period number, and e_t *was* the random error. Since cos(f t + d) = cos(f t) cos(d) − sin(f t)sin(d), this model can be rewritten as

$$x_i = \mu + a \cos(f t) + b \sin(f t) + et \tag{2}$$

where a = R cos(d) and b = −R sin(d). For a time-series signal, we have the k multiperiodic terms with different frequencies.

2.2 CropS2S Model Building

In remote sensing temporal data, cropland contains rich phenological information, which is not fully and deeply applied in current algorithms. At the same time, cropland will have different states within a time series cycle, and the land use status at different time nodes is mutually influential. The corresponding output should be a sequence that can represent the changes in land use status. Based on this, a sequence to sequence (Seq2Seq) model was proposed, using attention mechanism to improve attention to phenological features and achieve output of cultivated land change status.

The model was built on the basis of the Seq2Seq model and introduced an attention mechanism to solve the problem of insufficient attention to the trajectory characteristics of cropland phenology. This project intended to adopt a model structure as shown in the figure. The encoder and decoder were composed of three layers of LSTM, respectively. The encoder received the phenological trajectory time series of pixels and extracted the land information contained therein. The decoder obtained a fixed length sequence of cultivated land change status based on the dynamic encoding vector ct. The LSTM used a bidirectional LSTM with 240 hidden layer units. In order to maintain the simplicity of the graph, only the "forward" LSTM was drawn. In addition, the design of LSTM loop feedback enabled it to handle any length of time series. At the same time, research was conducted on the network structure and number of network layers for automated determination of joint feature extraction of spatial spectral and phenological information.

3. Experiment

3.1 Study Areas and Data Preparation

The study area was located in the the Taihu Lake basin, covering an area of 36900 square kilometers. It belongs to Jiangsu, Zhejiang, Shanghai and Anhui provinces (cities). It is the most densely populated area of large and medium-sized cities with the most dynamic economy in China.

The Taihu Lake Lake basin is a dish shaped terrain with high surrounding, low middle, high west and low east. The western part of the basin is mountainous, accounting for about 20% of the basin area. The central and eastern parts are plain river networks and depressions and lakes centered on the Taihu Lake Lake. The north, east and south sides are affected by the sediment accumulation of the Yangtze River and Hangzhou Bay. The terrain is high, forming a dished edge. The central and eastern parts account for about 80% of the basin area. The the Taihu Lake Lake basin belongs to the subtropical monsoon climate zone, with four distinct seasons and abundant rainfall. The average annual precipitation in the basin is 1206 mm, and the average annual natural runoff is 18.82 billion cubic meters.

The Landsat image of the research area in 2009 has a regional range of 4695 x 5052 pixels and a coverage area of approximately 141km x 151km. Between 2009 and 2017, due to the accelerated urbanization process, the built-up area of the research area continued to expand and the cultivated land area significantly decreased. To verify the effectiveness of the continuous change detection method, a total of 20 Landsat

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interannual time series data and 10 SAR image from 2009 to 2017 were collected in the study area for continuous dynamic monitoring of cropland.

Remote sensing images required a certain degree of preprocessing before processing, in order to achieve better radiometry uses the Sentinel series data processing software SNAP product data, there was still a large amount of thermal noise in GRD products that required multiple repeated processing. Except for image cropping using ENVI 5.3 software, all other operations were performed using SNAP software.

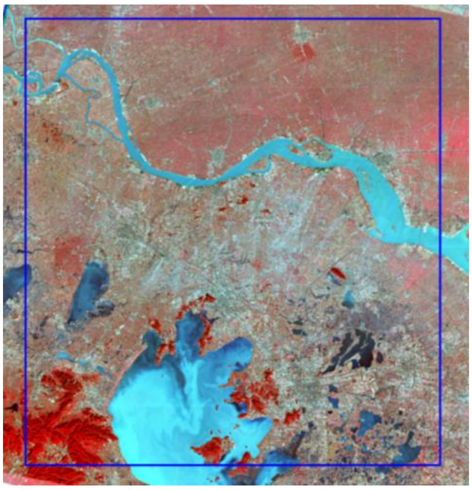

Figure 3. Study areas located in Taihu Lake

3.2 Experimental Results and Discussion

The proposed method can provided change information and classify image images as new images were acquired. The change image and classification image of the research area were shown in the figure. In order to highlight the continuous change information each year, this article used different colors to mark the change areas each year. From the entire change image, it can be seen that the study area experienced the most changes from 2010 to 2011 (in the green area), with a significant reduction in arable land coverage; The second time range with significant changes is from 2014 to 2015 (magenta). In order to visualize the experimental results more clearly, this article selects two sub regions A and B at different positions in the study area for zooming in display. The timing and types of changes in cropland vary in different regions.

Figure 5 shows the detailed change information of sub region A, with the first row displayed images from different years and Google Earth images; The second row was a change image. From the image, it can be seen that this area has been transformed from farmland to bare land since 2011 and then rapidly into water in 2012, with the entire transformation process occurring between 2011 and 2012. The blue area in the change image was the result of continuous change detection. At the same time, it can be clearly seen that the pixels in this area showed a periodic trend of cultivated land change from 2009 to 2011. After the change occurred in 2011, the pixel value rapidly decreased, and between 2012 and 2017, it showed a trend of changes in the built-up area. Therefore, the proposed method accurately detects the time, range, and intensity of changes in cultivated land.

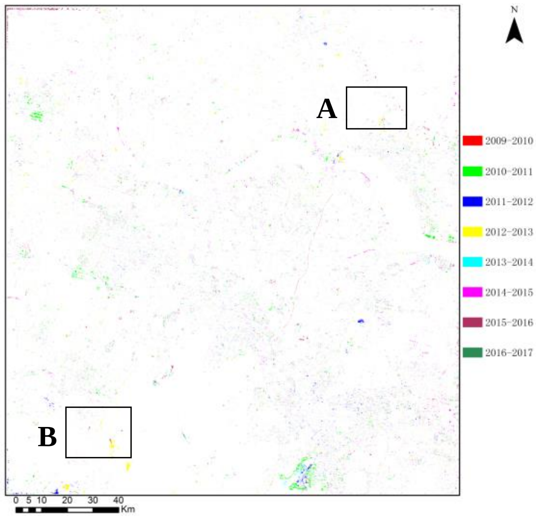

Figure 4. cropland change areas from 2009-2017

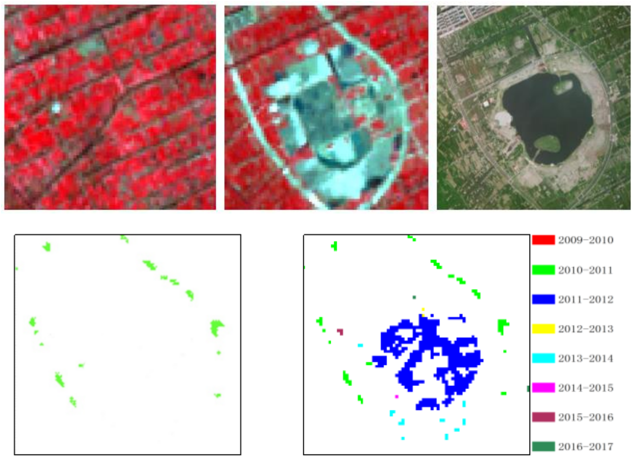

Figure 5. Region A: cropland change areas from 2009-2017

Figure 6 showed the change information of sub region B, where Landsat images and corresponding change images were collected every two years. From the graph, it can be seen that although the types of pixel changes were from cropland to built-up areas, the time of change was not entirely consistent. The cropland in region 1 has already undergone changes since 2011, the cropland in region 2 has been changing since 2013, and the cultivated land in region 3 only began to change in 2015. The corresponding change images show the changes from 2009 to 2011, 2009 to 2013, 2009 to 2015, and 2009 to 2017, respectively. The cropland in different regions gradually changes at different times. In addition, the specific time and intensity of pixel changes in the three regions were also displayed on the EVI temporal trajectory. Region 1 mainly underwent changes in the second half of 2010, and the numerical range rapidly decreased from 0.4 cropland in Region 3 only began to change in mid-2015, and the EVI time series trajectory fluctuated around 0 values.

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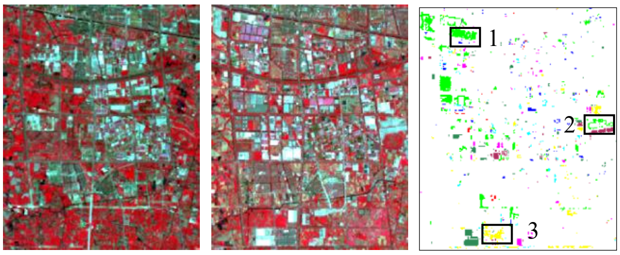

2009 2017 change areas

Figure 6. Region B: cropland change areas from 2009-2017

3.3 Accuracy Evaluation

Due to the use of long-term data to detect changes in cropland in this article, it was extremely difficult to find historical reference data that can fully evaluated the detection accuracy. In the time range of 2009-2017, there were almost no data with higher spatial and temporal resolutions than Landsat data. In order to obtain the time and location of surface cover changes, the main source of reference data can only be Landsat data itself. High spatial resolution Google Earth imagery was beneficial for manually interpreting land cover types. Even though it was difficult to obtain annual Google Earth historical images, relatively high spatial resolution was still beneficial for identifying information on land cover changes. In order to quantitatively evaluated the accuracy of continuous change detection methods, this paper adopted the random box proportion method to evaluate the accuracy of change detection. Within the 30 divided grids, randomly selected 1000 training samples, including 500 unchanged training samples and 500 changed training samples; Then calculated the confusion matrix between manual interpretation and change detection results. The results were shown in Table 22.

Manual interpretation										total	User accuracy
Change detection	NC*	2010	2011	2012	2013	2014	2015	2016	2017		
NC*	861	92	36	32	12	26	41	18	3	1121	0.77
2010	0	123	0	0	0	0	0	0	0	123	1.0
2011	2	0	112	11	0	0	0	0	0	125	0.89
2012	1	0	0	198	0	0	0	0	0	199	0.99
2013	6	0	0	0	161	0	0	0	0	167	0.96
2014	1	0	0	0	3	135	0	0	0	139	0.97
2015	7	0	0	0	0	0	236	0	0	243	0.97
2016	1	2	0	0	0	0	0	230	0	233	0.98
2017	3	0	0	0	0	0	0	0	123	126	0.97
total	882	217	148	241	176	161	277	248	126	2476	
producer accuracy	0.97	0.56	0.75	0.82	0.91	0.83	0.85	0.92	0.97		
Overall user accuracy：0.84						Overall producer accuracy：0.94					
overall accuracy：0.88						Kappa：0.85					

Table 1. Classification results of land cover data

From the table, it can be seen that the method proposed in this article achieved an overall accuracy of 93.30% and a Kappa coefficient of 0.87. The high leakage error of changing pixels may be caused by two factors. Firstly, due to the relatively small amplitude of some changing pixels, the continuous change detection method ignores these changing pixels; The second reason was that the pixels have changed during the process of building the model. At the initial modeling stage, it was often assumed that the pixels involved in the modeling have not changed. Therefore, the changing pixels involved in modeling are also to some extent overlooked. The occurrence of misclassification rate was mainly due to overfitting of the time series model. Overfitting can amplify the magnitude of changes to a certain extent, leading to misclassification of invariant pixels. If the data disappeared within a specific time due to clouds or cloud shadows, the multi harmonic model was likely to exhibit overfitting.

4. CONCLUSION

We evaluated our proposed method on a High resolution remote sense dataset of land cover data. The experimental resulted show that our proposed method outperforms traditional methods and achieved high accuracy in identifying cropland change. In addition, we conducted a sensitivity analysis to evaluate the impact of different factors on the performance of our method. The results showed that our method was robust to changes in the input data and the network architecture.

The major contributions of this paper were summarized as follows: (1) our approach integrated information from multiple sources time-series data into a high spatiotemporal dataset, enabling effective fusion and mining of multi-source data. (2) In order to eliminate pseudo changes in cropland, the phenological features of cropland were introduced into deep learning models to improve the attention weights of features. The proposed method has several advantages over traditional methods. First, it was automated and did not require manual surveys, which can save time and cost. Second, it could provide a more comprehensive and accurate understanding of the spatial distribution of change. In future work, we planed to explore the use of additional data sources, such as INSAR data and Hyperspectral data, to further improve the accuracy of our method. Overall, our proposed method provided a promising approach for exploring cropland based on multi-source remote sensing images and cross-modal networks.

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