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Winter Wheat Yield Estimation from Multi-temporal Remote Sensing Images Based on Convolutional Neural Networks

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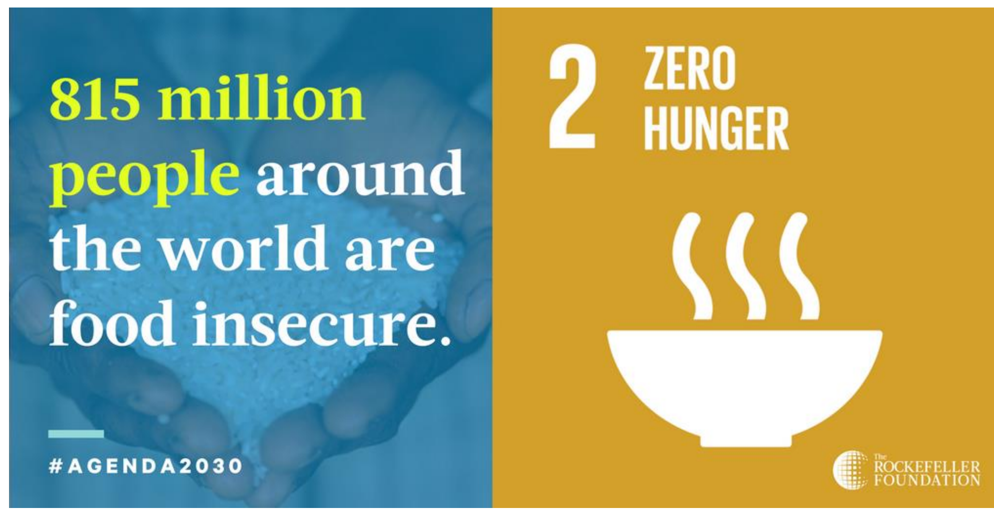
CONTENTS

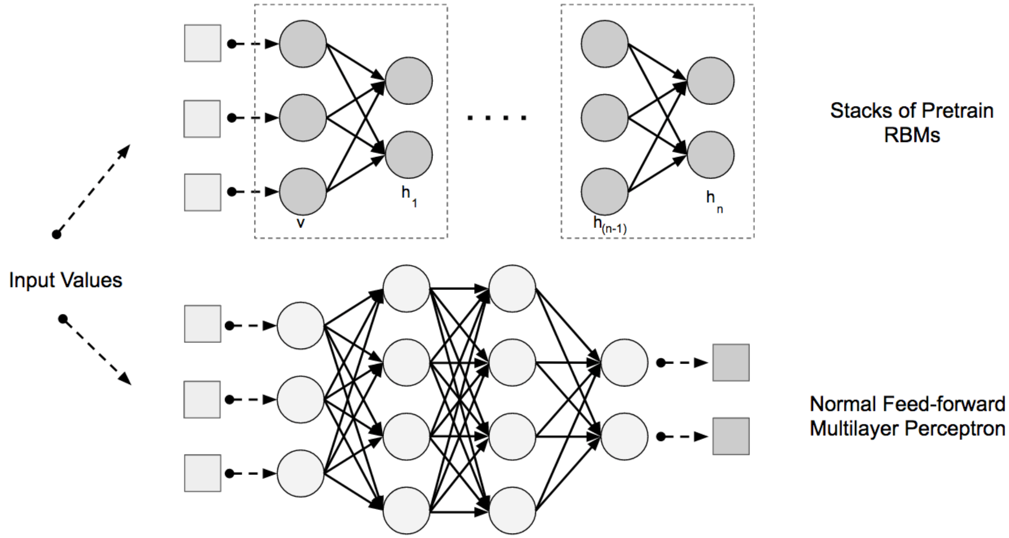
01 INTRODUCTION

Food is the basis of human survival and development. In recent years, tremendous efforts are needed to **end hunger, achieve food security and improved nutrition and promote sustainable agriculture[1].** **The key to these efforts is to timely and accurately estimate crop yields to regulate food market safety.**

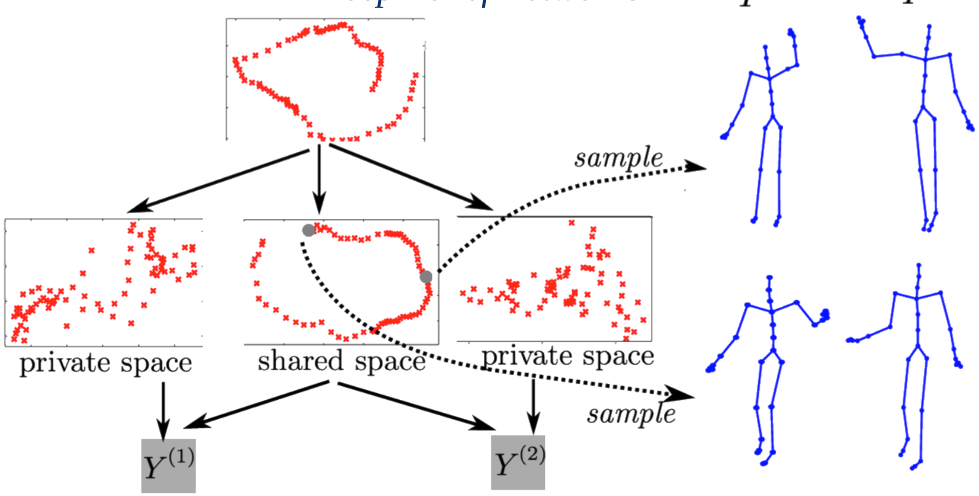


United Nations. “Transforming our world: The 2030 agenda for sustainable development,” General Assembley 70 session, 2015.

01 INTRODUCTION



Deep Belief Networks



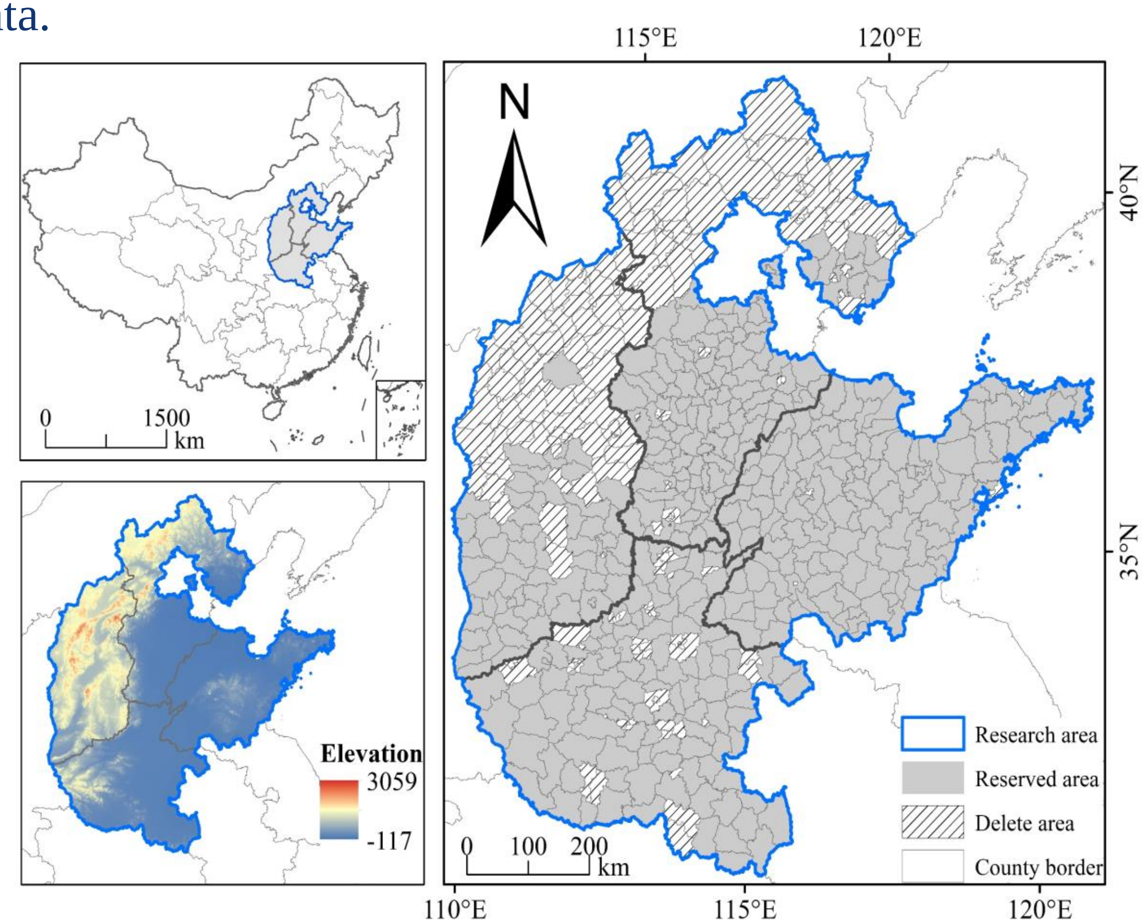
Deep Gaussian Process

In terms of agricultural remote sensing, yield estimation is always a core problem. Many scholars have proposed feasible and effective NN structures to achieve excellent performance in large-scale crop yield estimation. Such as *Multiple Restricted Boltzmann Machine (MRBM)*, *Spiking Neural Network (SNN)*, *Deep Gaussian Process (DGP)*, *Deep Transfer Learning (DTL)*, etc.

01 INTRODUCTION

In the field of DL, CNN has become one of the state-of-the-art algorithms. It is able to extract high-level semantic information from the basic features of the original pixels based on remote sensing data.

In this paper, ***North China*** *is* selected as the research area. Mainly including *Henan, Hebei, Shanxi and Shandong* provinces. Most areas of Shanxi and northern Hebei are removed by cleaning the statistical data. The main reason is that the altitude causes the winter wheat to be planted less, and secondly some areas with abnormal statistics are deleted.



02 DATA SETS

19 estimation indexes related to winter wheat growth were selected from **6 different MODIS products**.

The selected products include: **MOD09A1. MYD11A2. MOD13A1 and MYD13A1. MOD15A2H. MOD16A2. MOD17A2H.**

According to the growing season of winter wheat, the data time range is from **the 273rd day of the year to the 185th day of the next year.** The image data ranging from **2006 to 2016** are selected.

Therefore, The total experimental MODIS images amount to **6376**, and are processed by *Shell and GDAL*. Multiple types of images are **resampled, spliced and cropped**, and finally fused into **163,944** images that contain **19** bands.

02 DATA SETS

Band	Time(d)	Resolution(m)	Scale	Dimension-reduce range
sur_refl1(620-670 nm)	8	500	0.0001	1,5000
sur_refl2(841-876 nm)				
sur_refl3(459-479 nm)				
sur_refl4(545-565 nm)				
sur_refl5(1230-1250 nm)				
sur_refl6(1628-1652 nm)				
sur_refl7(2105-2155 nm)				
LST_Day	8	1000	0.02	13000,16000
LST_Night				13000,15000
ET	8	500	0.1	1,300
PET				1,800
LE			10000	1,800
PLE				1,2000
GPP	8	500	0.0001	1,200
PsnNet				1,350
NDVI	16	500	0.0001	1,9000
EVI				1,9000
FPAR	8	500	0.01	1,75
LAI			0.1	1,30

03 METHOD

We assume that the winter wheat yield is not related to the positions of the image pixels.

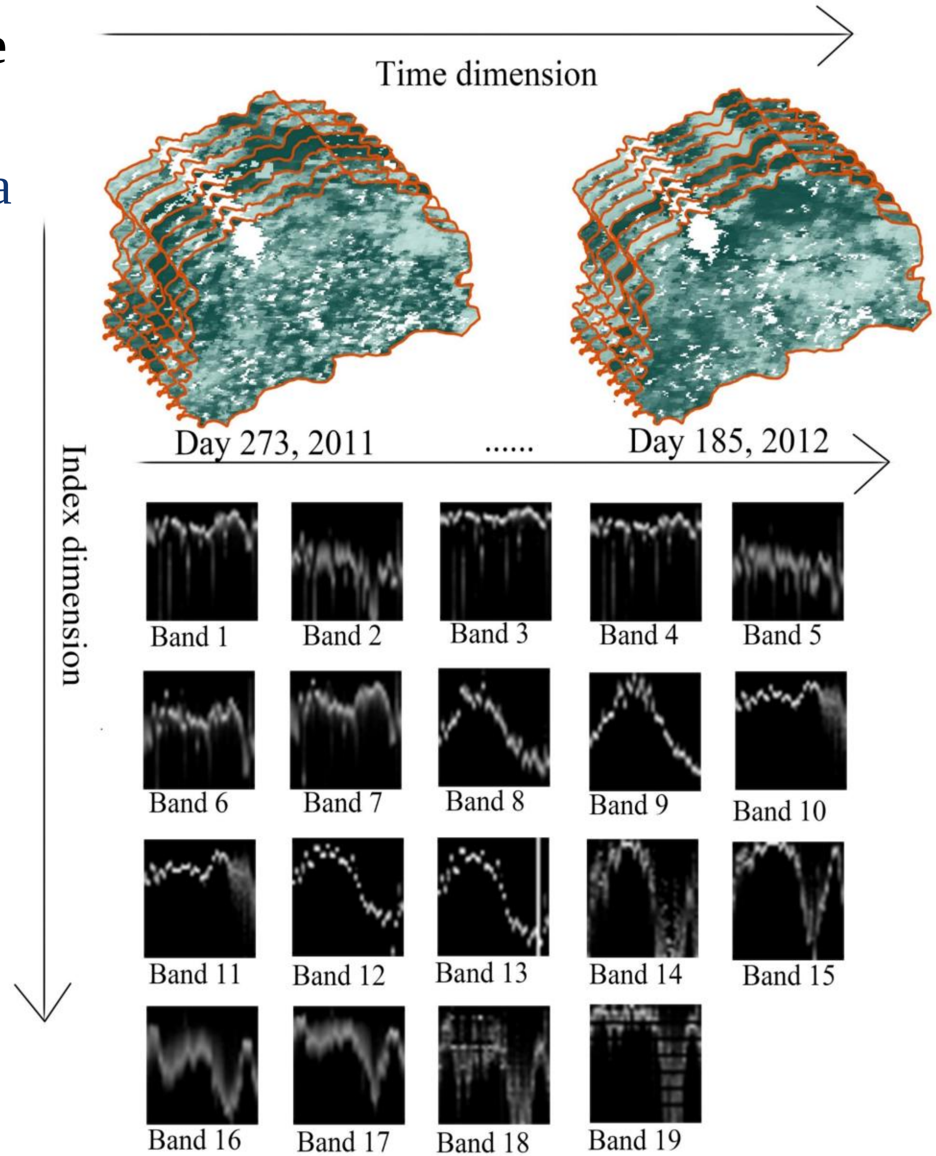
Based on this assumption, the histogram is utilized as an image feature since it contains no spatial information. It should be noted that the growth of winter wheat is only closely reflected by the partial value range of each selected index.

Therefore, the histograms - which contain 36 bins - are generated and normalized within the partial ranges of the selected indexes as shown in Table.

03 METHOD

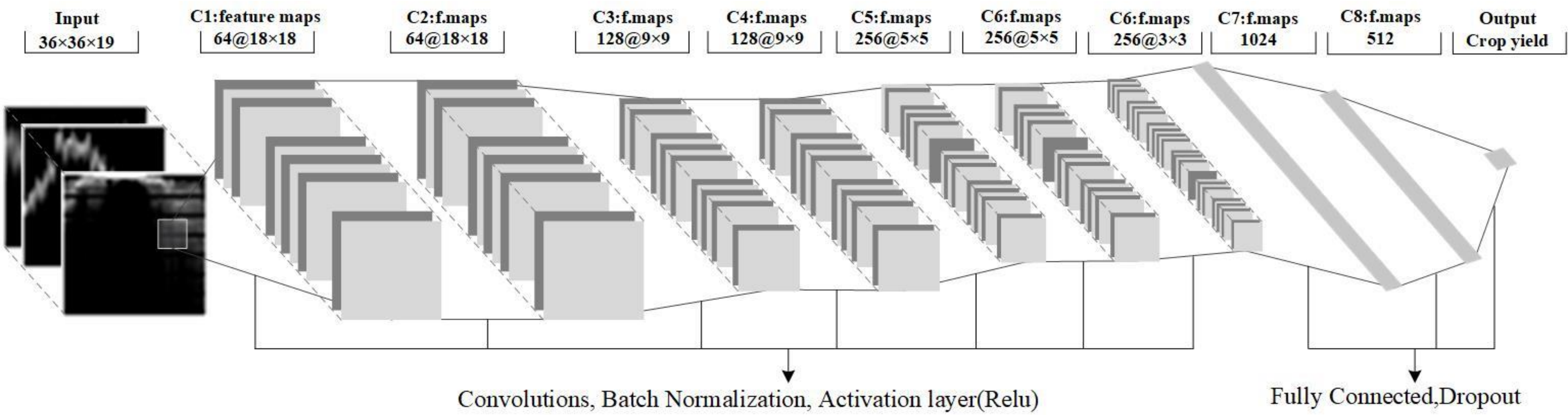
Taking the county of **Henan Province** as an example to illustrate the sample generation process, each county produces a sample in a growing season.

Each index shown in Figure is synthesized into a 36×36 matrix in the time dimension. Finally, the 36×36×19 three-dimensional matrix generated by the 19 bands serves as the input layer of CNN. The output layer employs the corresponding winter wheat yield statistics (in kilograms per hectare) to generate a CNN sample.



03 METHOD

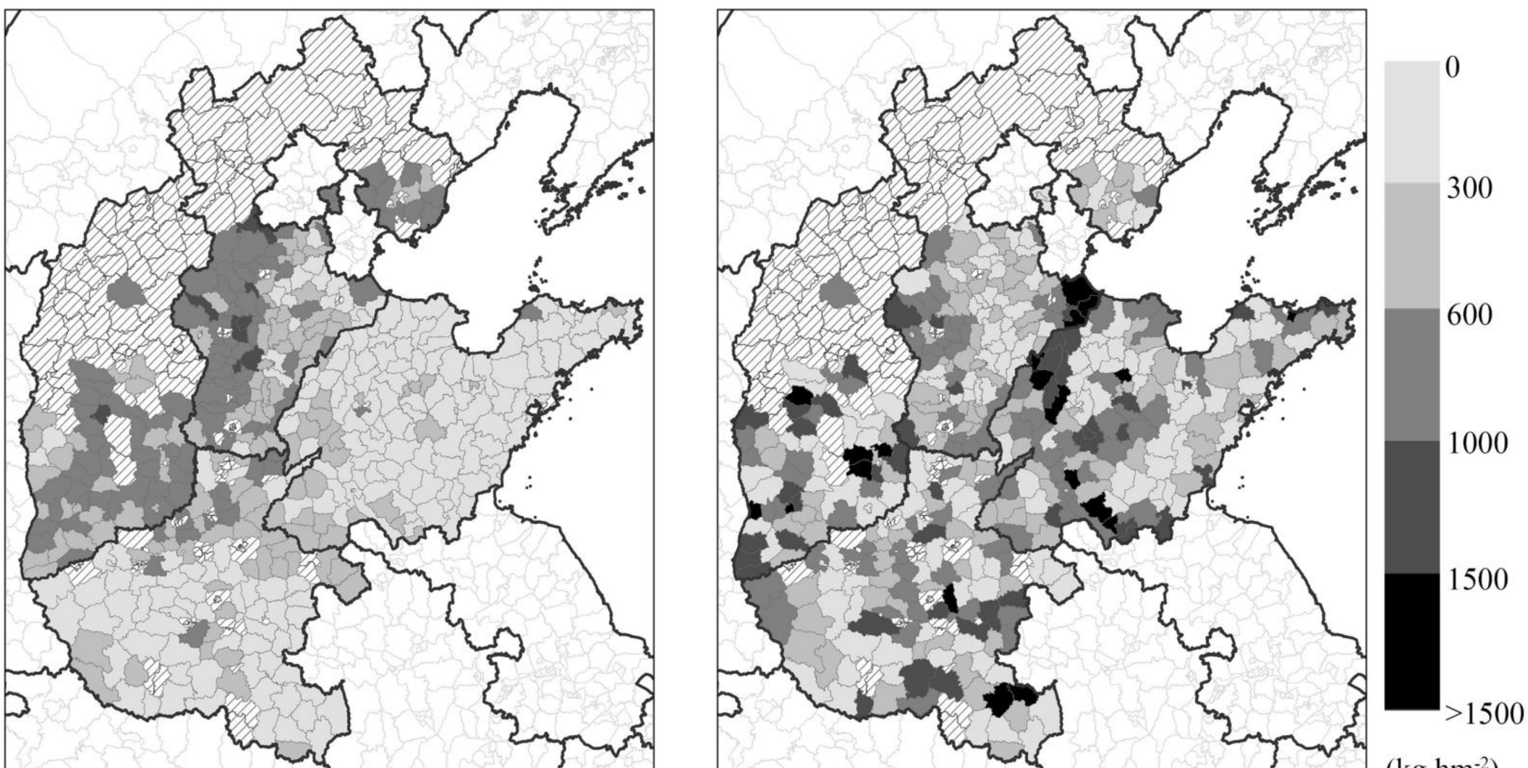
The applied convolutional neural network is designed according to the characteristics of the generated samples, and **the small convolution kernel is used**. The multi-layer stacking of the convolution kernel reduces the number of parameters, increases the network depth and enhances the network capacity and complexity, and thus fits the complex process of crop growth.



Regression-based convolutional neural network structure

04 EXPERIMENTAL RESULT

Taking the year 2016 as an example(Shandong Province is 2010), the spatial distribution of the model error in the training set is shown in Fig.(a). The spatial distribution of the model error in the validation set is shown in Fig.(b).



(a)Training Set Error Spatial Distribution

(b)Validation Set Error Spatial Distribution

04 EXPERIMENTAL RESULT

The results in the training set are shown in Table 1. It achieved good performances in different areas. The model performance of the validation set is shown in Table 2.

TABLE 1. MODEL ERROR IN TRAINING SET

	Henan	Hebei	Shandong	Shanxi	North China
Pearson's r	0.98	0.93	0.94	0.95	0.93
RMSE	242.39	425.21	300.19	534.99	386.46

TABLE 2. MODEL ERROR IN VALIDATION SET

	Henan	Hebei	Shandong	Shanxi	North China
Pearson's r	0.87	0.78	0.56	0.69	0.82
RMSE	657.93	586.80	758.14	963.05	724.72

04 EXPERIMENTAL RESULT

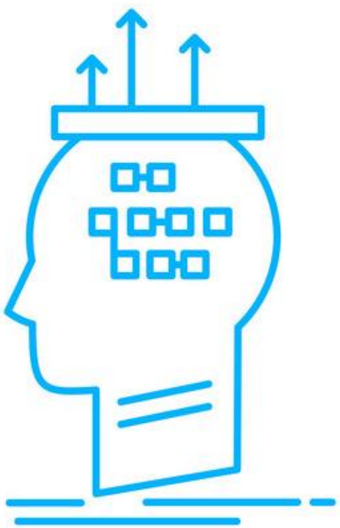
Robustness Verification

Training different models based on the neural network structure proposed in this paper without artificially setting hyperparameters. The important hyperparameters are as follows: learning rate is 0.001, weight decay is 0.005, and dorp out is 0.25. Verify the robustness of the model under conditions that guarantee the objectivity of the experiment. The training model is selected separately for five years. The Pearson's r of the validation set is high and the RMSE is around 1000 kg·hm^{-2}. The method of this paper has high robustness and can be used crop yield estimation in the future.

TABLE. MODEL ROBUSTNESS VERIFICATION

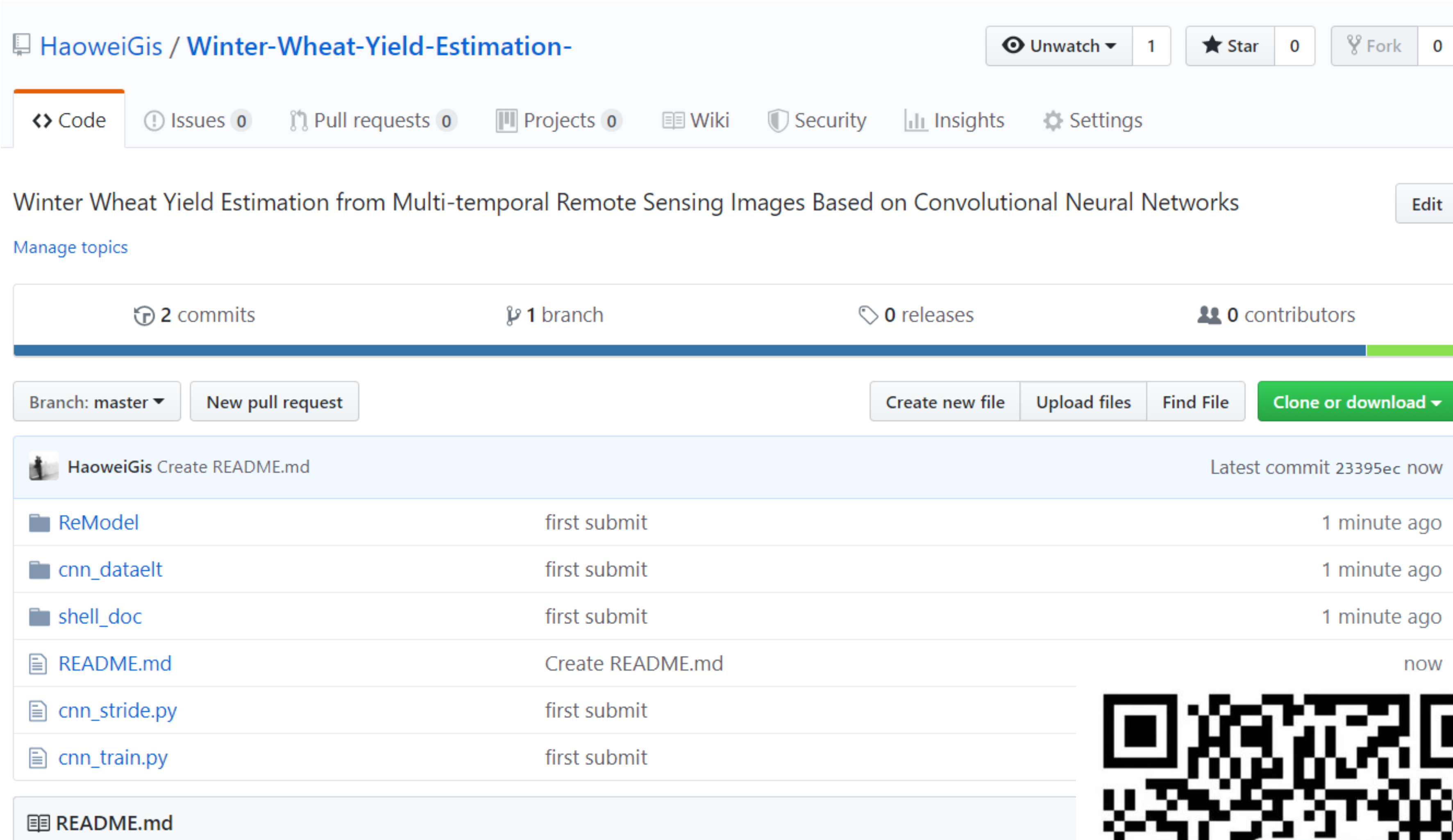
	2006	2008	2010	2012	2014
Pearson's r	0.55	0.71	0.67	0.76	0.76
RMSE	1081.78	992.38	1074.49	938.52	945.89

05 CONCLUSION AND DISCUSS



CNN is able to effectively extract the features related to winter wheat yield from remote sensing images. It deals with the constraints of the traditional statistical model on the fitting of complex relationships and does not require field sample collection. **This end-to-end model has the advantage of synergism.** After sufficient and proper training, **the model is able to efficiently predict future winter wheat yield in a real-time manner.**

In this paper, the method of histogram extraction is used for dimensionality reduction of remote sensing images, which has a large loss of information. In the process of sample generation, outliers are produced in the time dimension. Therefore, it is possible to consider a more advanced algorithm for *dimensionality reduction* and *time series smoothing* in ***future research.***



https://github.com/HaoweiGis/Winter-Wheat-Yield-Estimation


THANK YOU