PREDICTION OF CORN YIELD IN NEW YORK STATE BY HARNESSING SATELLITE REMOTE SENSING AND DEEP LEARNING

A Thesis

Presented to the Faculty of the Graduate School

of Cornell University

in Partial Fulfillment of the Requirements for the Degree of

Master of Professional Studies in Agriculture and Life Sciences

With a Specialization in Geospatial Applications

by

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May 2022

ABSTRACT

The forecast of crop yield is of great significance to improve agricultural production efficiency. It not only affects the local economic development, but also is closely related to human life. With the significant growth of open-access high-resolution real-time remote sensing observations from satellite missions and the broad applications of machine learning techniques, the combination of the two technologies offers a promising solution for crop yield estimation. Based on the land surface temperature data and surface reflectance data obtained by Moderate-Resolution Imaging Spectroradiometer (MODIS), this study aims to estimate the corn yield in New York State at the county-level by using Convolutional Neural Network (CNN) integrated with a Gaussian Process (GP) model that can improve the accuracy of spatio-temporal structure modeling. My results show that the CNN-GP integrated model can improve the prediction accuracy by 18% relative to CNN alone, indicating the potential of harnessing satellite remote sensing and deep learning to inform decision making at both field and regional scales.

BIOGRAPHICAL SKETCH

Tianqi Kuang was born on September 24^{th} 1998 in a middle part of Chinses city, Xiaogan. Growing up in an open and friendly family atmosphere, Tianqi has been educated by the concept of "reading thousands of books and traveling thousands of miles" since she was a little girl. Her parents take her to travel around the world every holiday to feel the local customs and history, so that her childhood is spent in a happy and relaxed experience. While learning more knowledge from nature, it also cultivated her interest in geography. She went to university in Suzhou, Jiangsu, a famous cultural city in a Water Town of Yangzi River, and chose Geographic Information Science as her major, which facilitates her to learn geographic knowledge more systematically, as well as better combine these knowledges with modern science and technology then apply them to real life. Therefore, during her undergraduate period, she participated in many academic competitions and achieved some progress in the field of water pollution control and vegetation monitoring interacted with GIS. In order to get further research, she came to the school of agriculture and life sciences in Cornell University to pursue a master's degree. Under the careful guidance of her advisor Dr. Sun, she has mastered more knowledge and skill in remote sensing, geospatial big data analysis and agroecosystem, which is the theoretical and applied basis for her to solve practical problems.

ACKNOWLEDGEMENT

What I want to appreciate most is my advisor Dr. Sun. Her professional knowledge and rich practical experience in agricultural ecosystem and climate have provided me with a lot of help. In addition, her rigorous scholarship and serious working attitude are good examples, which are worth learning for my whole life. The determination of the theme of this article, the choice of theory and the application of research methods have been guided by her patience. Every time I talk to her, she can point out my problems in time and remind me of the direction of improvement. When I encounter difficulties, she can always give me support and encouragement at the first time, so that I have more sufficient motivation to think continuously and explore deeply to find solutions. The two years of studying with her have really benefited me a lot.

I also want to thank my parents. They not only ensured my abundant material resources, enabled me to study and live in the United States without worry, and had the opportunity to see the broader world, but also gave me constant spiritual and emotional support when I was studying in a foreign country alone, so that I had the courage to overcome difficulties and move forward bravely. While studying in Cornell, I also met many like-minded friends. Exploring and discussing new knowledge with them broadened my horizons and made my life more colorful.

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LIST OF ABBREVIATION

Moderate-Resolution Imaging Spectroradiometer (MODIS)

Convolutional Neural Network (CNN)

Gaussian Process (GP)

Remote Sensing (RS)

Geographic Information Systems (GIS)

Global Positioning System (GPS)

Normalized Difference Vegetation Index (NDVI)

Vegetation Indices (VIs)

Support Vector Regression (SRV)

Deep Learning (DL)

Machine Learning (ML)

Multi-layer Perceptron (MLP)

Long Short-Term Memory (LSTM)

Extreme Gradient Enhancement (XGBoost)

Random Forest (RF)

Root Mean Squared Error (RMSE)

Mean Absolute Percentage Error (MAPE)

Cropland Data Layer (CDL)

National Agricultural Advisory Service (NAAS)

United States Department of Agriculture (USDA)

Google Earth Engine (GEE)

1. Introduction

1.1 Research Background

Grain production is the basis and guarantee for the realization of national economy and development, and is closely related to human wellbeing. However, in the field of agriculture, natural disasters and other factors can lead to grain production failure, and then affect the national economy and the people's livelihood. Therefore, how to estimate the yield of crops in time and effectively to obtain grain information has always been the focus of Agriculture.

The traditional methods rely on field data collection, which is labor intensive and costly. Therefore, it is necessary to develop efficient and convenient new technology to improve the yield estimation. With the rapid development of remote sensing (RS) technology, the monitoring information needed in agricultural production can be obtained quickly and efficiently. Remote sensing technology has the characteristics of rich information, near-global coverage and short update cycle. Therefore, remote sensing technology provides a reliable resource to assist accurate and rapid acquisition of crop planting area, crop growth monitoring and crop yield estimation, and its in-depth application in the field of agriculture promotes the development of traditional agriculture to modern agriculture. In recent years, the continuous development of neural network provides new ideas for solving the problems in global agricultural production. Unlike multiple regression analysis, which can only deal with linear relationship, neural network can better characterize nonlinear relationship. Therefore, the combined application of neural network and remote sensing data has gradually become increasingly popular to resolve challenges in agricultural monitoring.

As the world's largest corn producer and exporter, the United States supplies more than 30% of the world's corn production. Therefore, accurate and timely estimation of corn production in the United States is very important for farm resource management, food security monitoring and market planning. In addition, because of global warming and climate extremes, corn production in the United States has decreased significantly. Therefore, the large-scale seasonal prediction of maize yield can help evaluate response to environmental stress, and therefore provide solutions for sustainable agricultural planting systems more efficiently.

1.2 Research Status

The traditional yield estimation methods include statistical investigation methods, meteorological prediction methods, agronomic prediction methods and so on. The statistical investigation method directly combines the influencing factors in the process of crop yield formation such as temperature, precipitation and sunshine with yield to build a yield estimation regression model. The principle of this method is simple, but it lacks mechanism, so it is difficult to achieve the ideal effect in practical application. Agronomic prediction method is based on the mechanism of crop yield formation, which has high yield estimation accuracy and good prediction effect. However, due to the need for a large number of relevant parameters as input of influencing factors, it is difficult to obtain and the process is cumbersome, so it is difficult to be widely used and popularized. The meteorological forecast method uses the meteorological factors affecting the yield to predict and forecast the yield. It has been relatively mature in the meteorological field, but this method is greatly affected by the meteorological data. The lack of meteorological data and meteorological stations limits the application scope of this method. Generally, the traditional crop yield estimation is mainly based on field investigation. Although it has high yield estimation accuracy, parameter acquisition usually requires a lot of personnel and equipment, which is time-consuming, laborious and costly. At the same time, with the continuous development of agriculture and the emergence of various food crises, the monitoring and evaluation of large-scale crop yield per unit area has become a new demand of modern agriculture. In this case, the traditional crop estimation methods cannot meet the dynamic requirements of crop yield estimation, and even limit the development and application of crop yield estimation.

With the continuous development of remote sensing (RS), geographic information systems (GIS) and global positioning system (GPS), the research on crop yield prediction using these technologies has made great progress. Especially in recent years, with the in-depth research of machine learning, deep learning and other ideas in various fields, it provides a new idea for using remote sensing information to realize real-time and accurate yield prediction. Machine learning model attempts to estimate yield by establishing the empirical relationship between yield drivers and historical yield, so it has the advantage of predicting crop yield without relying on crop specific parameters.

Mkhabela et al. (2011) calculated the normalized difference vegetation index (NDVI) using MODIS Image data, and used it as the core parameter to build a linear model to predict the yield of various crops on the Canadian prairie. Bolton and Friedl

(2013) derived multiple vegetation indices (VIs) from MODIS data to predict the yield of corn and soybean planting areas in the United States. In addition, in order to comprehensively consider more information related to plant growth, some scholars have also developed and explored nonlinear machine learning models, which can simulate more complex yield prediction processes. Johnson (2014) used the tree-based regression model, added climate factors as input parameters, and applied different remote sensing products to evaluate the accuracy of the yield estimation model. Kamir et al. (2020) established a support vector regression (SRV) model based on MODIS satellite images and climate records to explain the causes of yield changes in the Australian wheat belt.

In recent years, due to its powerful data processing ability and efficient algorithm, deep learning (DL) has gradually attracted extensive attention in the field of yield prediction. Compared with general machine learning (ML), DL method can fit more complex nonlinear relationships more accurately. Khaki and Wang (2019) developed a fully connected multi-layer perceptron (MLP) to predict the yield of corn hybrids on American farmland, considering the effects of soil and weather factors.

Jiang et al. (2019) established the Long Short-Term Memory (LSTM) model based on phenology in 9 states in the Midwest of the United States, and achieved the yield prediction of rain fed corn at the county level. Kang et al. (2020) used a variety of deep learning methods such as SVR, extreme gradient enhancement (XGBoost), random forest (RF), LSTM and CNN to predict the county-level corn yield of 12 states in the Midwest of the United States, and achieved the accuracy of RMSE of 1.10 T / ha.

1.3 Research objectives

Although these studies have achieved some success, there is still a lack of relevant research on yield prediction in New York state. Therefore, I aim to predict the yield of corn, the main crop in New York State Based on CNN, a typical and widely used deep learning algorithm. This model can overcome the scarcity of training data through dimension reduction. I also incorporate a Gaussian process to account for the temporal and spatial dependence between data points, to increase prediction accuracy. Finally, I evaluate the performance of this approach in predicting county-level corn yield, and compare the benefits of including GP in the prediction.

2. Materials:

2.1 Study Area

In this study, New York state was selected as the research area, and used the average yield of corn-growing region in 45 counties as the research object (Figure 1).

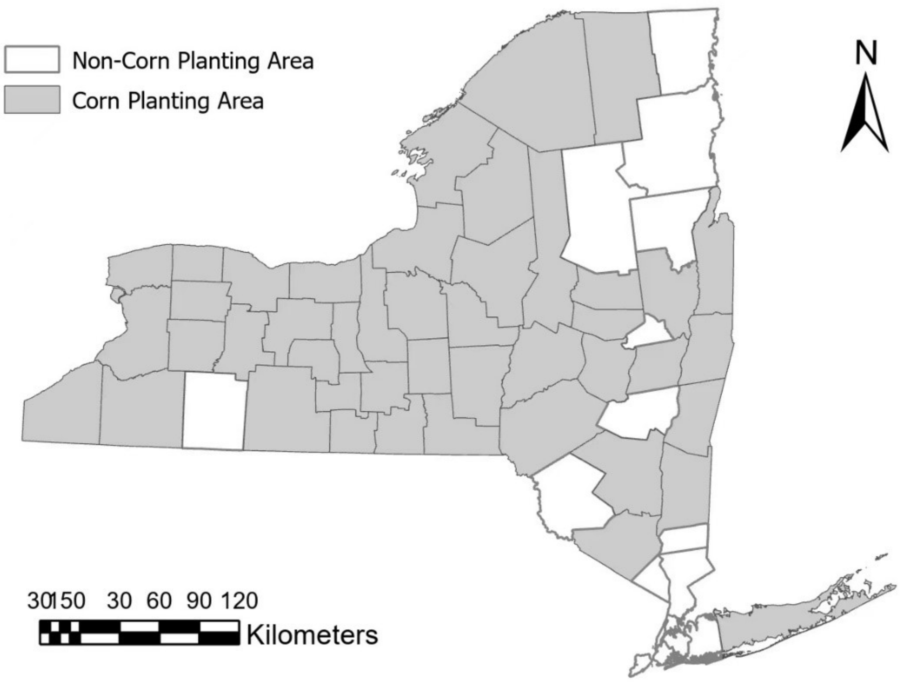

Figure 1. Distribution of corn growing areas in New York State

Agriculture is a $3.6 billion industry in New York State. With more than 35,000 farms, covers 7.8 million acres. The land consists of fertile soils and receives adequate rain, making it ideal to grow a wide diversity of crops from fresh fruits and vegetables, to forage and grains for livestock (New York State Department of Agriculture & Markets).

Corn is a major field crop in New York state with more than 1 million acres planted annually. Typically, grain corn (including dry-shelled and high-moisture) represents 55% of the acreage, whereas corn silage represents the remaining 45%. Recently, corn has been a very profitable crop to grow because of relatively high yields as well as high prices received by farmers. Although corn is a profitable crop on New York farms, it is also an expensive crop to produce (Cornell University, College of Agriculture and Life Sciences Website).

2.2 Data Source and Collection

Datasets used in this study include three groups: county-level crop yield from USDA NASS statistics, satellite images from 2012 to 2021, crop types at 30m from cropland data layer (CDL).

- The crop yield dataset mainly includes the average yield of corn at the county level in New York State in a decade from 2012 to 2021. According to the survey results, the overall corn yield in New York state shows an upward trend.
- Satellite data includes MODIS products, including MOD09A1 and MYD11A2 Among them, MOD09A1 product provides the estimated value of surface reflectance of MODIS band 1-7 at 500m resolution, and has been corrected for atmospheric contamination. MYD11A2 product provides average surface temperature with 1km resolution. The temporal resolution of these remote sensing images is 8 days. We only use satellite images taken during corn growth from March 10^{th} (69^{th} day) to October 4^{th} (276^{th}). Therefore, in this study, satellite images are collected 26 times a year, and all multispectral images are discretized using 32 bin to generate 3-D histogram.
- CDL is downloaded from the National Agricultural Advisory Service (NAAS) in United States Department of Agriculture (USDA), which include crop-specific land cover data that are produced annually for different crops based on moderate resolution satellite imagery and extensive agricultural ground truth. In this paper, the farmland data layer is used for corn, only focusing on the farmland in each county, and excluding non-farmland areas such as buildings and streets from

satellite images.

2.3 Data Preprocessing

The acquisition and pre-processing of remotely sensed surface-reflectance data is the critical initial step. Due to different sensor angles and the influence factors of atmospheric background and aerosol, some noise will be generated in the directly downloaded remote sensing image. Direct application may lead to the loss of key information, resulting in large error of calculation results. Therefore, it is necessary to preprocess the data in the early stage, including filtering, normalization, atmospheric correction Image clipping, etc. The specific steps are as follows:

- Apply QA band quality control, cloud removal and image normalization for MOD09A1 and MYD11A2 products on Google Earth Engine (GEE) platform.
- Clip New York State using the TIGER US Census data (2018).
- Filter multi-spectral images collected 26 times a year, from March 10th (69th day) to the October 4th (276th day) at the 8-day intervals.
- Convert the unit of reflectance and temperature for model training.
- Extract corn planting area only from CDL.

3. Research Method

3.1 Model Overview

Deep learning models can be viewed as complex non-linear mappings that can learn hierarchical representations of the data. CNN has been widely applied in image processing. It can simplify a large amount of data by dimensionality reduction, preserve image accuracy and improve computational efficiency.

CNN is mainly composed of three types of layers: convolutional, pooling, and fully connected. The convolution layer is responsible for extracting local features in the image, and the pooling layer is used to greatly reduce the order of parameters, which called dimensionality reduction. The full connection layer is similar to the traditional neural network part, which is used to output the results. Convolution layer is used for feature extraction. In this study, I take tensor $x \in R^{h*w*d}$ as input, and then the results processed by convolution layer are down sampled through ReLU function or max-pooling layer to avoid over fitting. After this step, the tensor $c = p(f(w * x + b))$ can be obtained.

Where $p(\cdot)$ is pooling function, $f(\cdot)$ is the nonlinear function. W is the weight matrix, which defines the filter of the convolution layer, $*$ is a two-dimensional convolution operator, which operates on $\hbar$ and w and d is the deviation term.

3.2 Gaussian Process Modeling

Based on the results of CNN simulation, this study uses Gaussian Process (GP) layer to further fit the calculation results. Due to the consideration of the dependence of space and time between data points, the accuracy of the model can be improved.

GP is a highly expressive supervised learning method, which is also considered as nonparametric machine learning technology. Compared with the general neural network, GP has much less parameters to learn, and the prediction is mainly driven by the data set they define. Because the GP belongs to the forward method, the training data can be directly used to make prediction, and the edge likelihood function can be used for second-order optimization. In addition, GP has good intuitive characteristics, that is, all interpolated average predictions are generated as a weighted linear combination of the existing average points in the training set, and are scaled according to the distance from the test point to the given data point. Therefore, the temporal and spatial correlation between adjacent sampling points can be better considered in this study. After the existing linear combination of points, the details of the difference can be retained.

The specific formula is:

$$g(x) = f(x) + \hbar(x)^T \beta$$

Where $x \in R^d$, $f(x)$ is a zero-mean GP modeling the residuals of a linear model, $h(x)$ is a fixed set basis function, and β is an independent random variable.

3.3 Model Development

3.3.1 Problem Setting

The purpose of this paper is to predict the average crop yield in the study area of interest based on remote sensing images and recorded data over the years. Therefore, the multispectral image sequence covering the study area of interest $(I^{(1)}, \ldots, I^{(\mathrm{T})})$ is used as the input, where $I^{(t)}$ represents the image of t period in a year, including the number of pixels in the horizontal (l) and vertical (w) directions of the image, as well as the number of bands (d) of each pixel, using $I^{(t)} \in R^{h*w*d}$ indicates.

In order to map the original image sequence to the county-level average crop yield, the historical yield related information needs to be introduced into the model. Therefore, we establish a training data set based on time series:

$$D = \left\{\left(\left(I^{(1)}, \ldots, I^{(T)}, g_{loc}, g_{year}\right)_1, y_1\right), \ldots, \left(\left(I^{(1)}, \ldots, I^{(T)}, g_{loc}, g_{year}\right)_N, y_N\right)\right\}$$

Where g_{loc}, g_{year} represents the spatial coordinates and year of the image respectively, y_i represents the real yield measured in the corresponding survey.

3.3.2 From Row Images to Histogram

Due to data limitation (D can be less than 10,000), I was unable to develop the direct end-to-end in-depth training model. Therefore, based on the premise of displacement invariance, the dimension reduction technology is adopted to make the average yield information and farmland location information independent of each other and improve the calculation efficiency. In order to map the high-dimensional image to the pixel count histogram without information loss, I assume that the pixel values in the digital image are discrete, and b different values can be taken in each band, which will directly lead to b^d bins in the histogram of each pixel. Based on the above assumptions, I discretize each band in a scene image and construct a histogram $\hbar_k \in R^b$, where k represents different bands in each pixel. By connecting the histograms of different bands $H = \left(\hbar_1, \ldots, \hbar_d\right)$, the original multispectral sequence image can be obtained, and the number of dimensions of the input data is greatly reduced.

3.3.3 From Histograms to Crop Yield

Although the amount of data is simplified, the input is still complex and highly nonlinear, which is not conducive to efficient deep learning. CNN provides an effective solution, i.e., stacking $\left(H^{(1)}, \ldots, H^{(T)}\right)$ into the form of 3-D histogram and use it as the input of CNN model. The convolution operation in the model is based on bin and time dimensions. The specific architecture is shown in Figure 2:

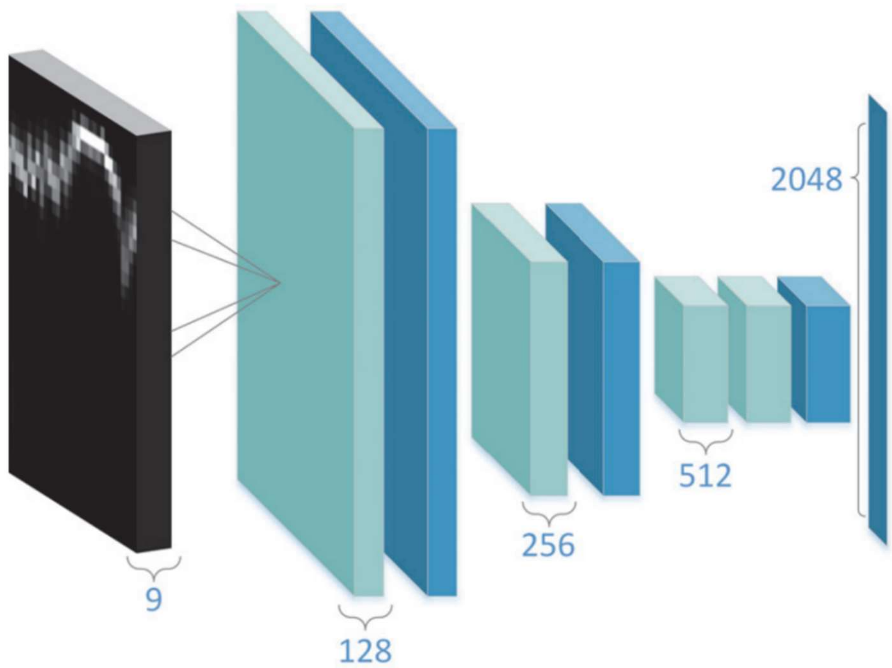

Figure 2. The CNN structure.

Because different locations in the histogram contain different geographic information, it is necessary to replace the pool layer by stride-2 convolution layer to avoid the influence of location invariance in the original pool layer. Thus I used the method called batch normalization to improve gradient flow and decrease half of speed to avoid overfitting.

3.3.4 Integrating the Spatio-temporal Information: Deep Gaussian Process

Much information related to crop growth, such as soil type and fertilization, cannot be obtained directly from remote sensing images, but it has a fixed relationship with geographical location and changes periodically with time. Considering this effect, the Gaussian process can reduce error corresponding to the adjacent points in space. In this study, I use the linear Gaussian process model, and replace the original parameters with the covariance depending on the space-time structure in the last layer of input.

3.4 Model Training

The preprocessed surface reflectance data, LST data and corn planting area extracted through CDL are used as input. In order to calculate the pixel histogram, 32 bins are used to discretize all remote sensing images to obtain the histogram $\left(H^{(1)}, \ldots, H^{(T)}\right)$ that can be used for model input. Because the time resolution of MODIS remote sensing image data used in this study is 8 days, and only 26 images are selected every year from 69$^{\text{th}}$ to 276$^{\text{th}}$ of corn growth period, $H^{(t)} \in R^{b*d}$, with b=32, d=9, T=26. In addition to this, the actual production data at the county level are from USDA statistical reports in bushels per acre.

3.5 Model Evaluation

After training the model, I use the following two metrics to evaluate the model accuracy, which are Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE).

(1) RMSE

Root mean square error has a very sensitive monitoring ability for the extreme value in the predicted value, so it is usually used as a detection method for the prediction ability of the model. The smaller the value of RMSE, the better the simulation effect of the model. Its calculation formula is as follows:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \widehat{y_i})^2}$$

Where y_i represents the actual output, $\widehat{y_i}$ represents the estimated yield, and N represents the number of samples.

(2) MAPE

MAPE is defined as the average of the absolute value of relative error, which is the ratio of the difference between the actual output value and the estimated output value. MAPE is an index used to evaluate the accuracy of prediction in the field of statistics, which can better reflect the accuracy of the estimated value. Generally, the smaller the MAPE, the higher the accuracy of prediction. Its calculation formula is as follows:

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{y_i - \widehat{y_i}}{y_i}\right|$$

Where y_i represents the actual output, $\widehat{y_i}$ represents the estimated yield, and N represents the number of samples.

4. Result

This project utilizes the yearly average corn yield ground truth output data from USDA website between 2012 and 2021 as the sample data of the experiment. In order to verify the accuracy of the model, the sample data is divided into training samples and test samples, that is, the data of the first five years of the test samples are used as the training samples to input the model, and the results are compared with the test samples to evaluate the accuracy of the model.

In order to further explore the influence of Gaussian process on the model output results, CNN and CNN + GP training data are used respectively to obtain the root mean square absolute value error, as shown in the Table 1 below:

Table1.
RMSE of county-level model performance (unit: bushels per acre)

Model / Year	CNN	CNN+GP
2017	6.13	5.96
2018	7.21	6.84
2019	5.76	5.65
2020	6.53	6.27
2021	5.42	5.23
Avg	6.21	5.99

As shown in the table, the RMSE level of CNN + GP over the years is better than that of CNN alone. The result explain that the model with Gaussian process has better fitting and more accurate prediction results.

In order to illustrate that GP can reduce spatial correlation error, the prediction results in 2021 are displayed through map visualization (Figure 3 and Figure 4) as the examples. The error is expressed as the absolute difference between the statistical value and the predicted value. It is apparent that errors are spatially correlated (Where blue means underpredicting and red means overpredicting). Through comparison, it is found that the prediction residual is substantially reduced after adding GP. More specifically, using the spatial autocorrelation (Global Moran's I) tool provided by ArcGIS to predict the spatial autocorrelation of errors, it is obtained that the z and p-value values of errors generated by using CNN model alone are less than CNN + GP model, indicating that GP can reduce the errors caused by crop growth related factors caused by soil and fertilization that cannot be obtained from remote sensing images.

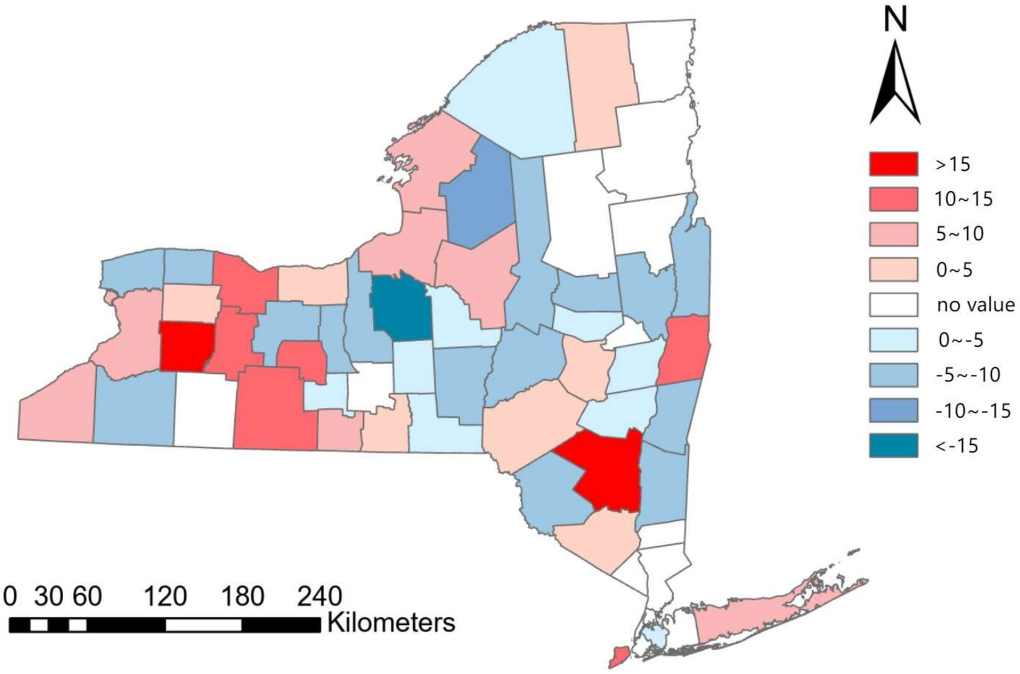

Figure 3. County-level error map of CNN model prediction. The color represents the prediction error in bushel per acre.

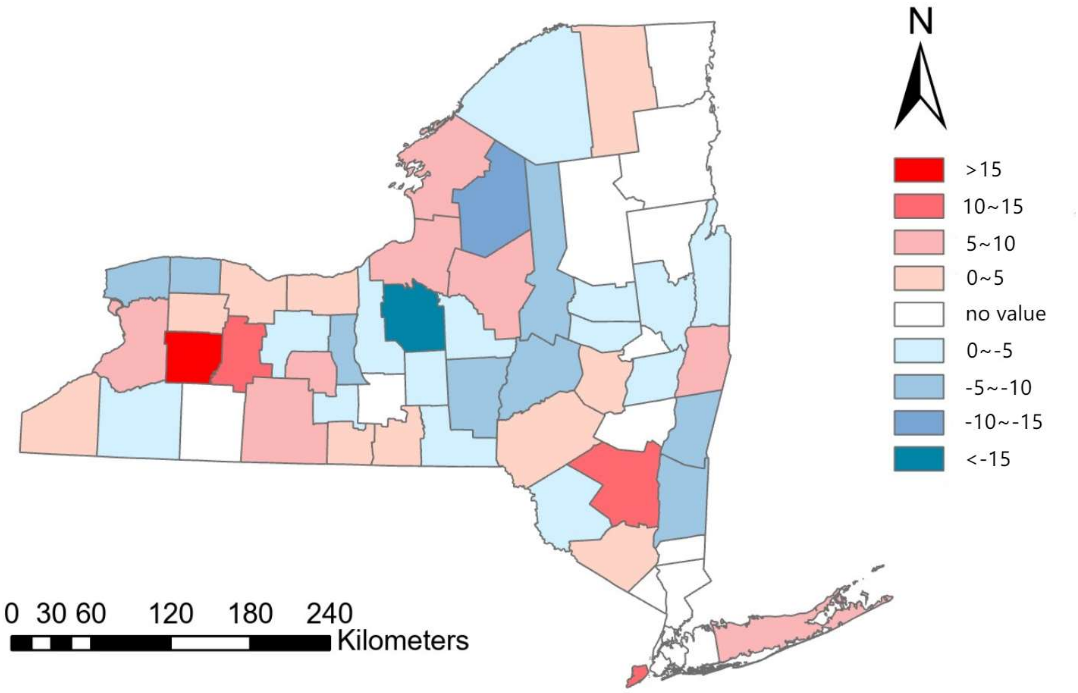

Figure 4. County-level error maps of CNN model prediction after adding the GP. The color represents the prediction error in bushel per acre.

July and August are the growing season of corn in New York State, and September and October are the harvest season. In order to further explore the impact of corn related growth factors on the prediction results and realize the early prediction as much as possible, only the subset of remote sensing image sequence $(I^{(1)}, \dots, I^{(t)})$, $t \in T$ is used as the input for testing. The prediction results are evaluated by the average RMSE over the years, and the results are shown in the Figure 5 below.

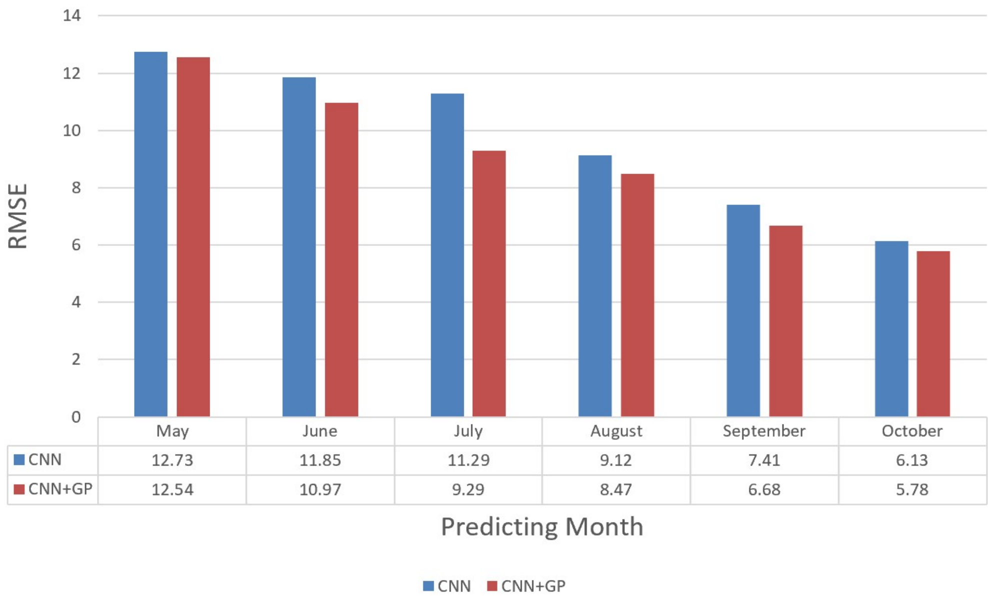

Figure 5. Model performance in each month measured in RMSE. The results are averaged from 2012 to 2021 and the unit of RMSE is bushels per acre .

Predicting month indicates that the images from the beginning of each year (i.e. March 10) to that month are used as the model input. The results show that the yield estimation accuracy of the two models increases with the increase of the number of images, which proves that the stability of early yield estimation is not high and needs more information related to growth as a supplement.

Finally, this study uses MAPE to measure the performance of this model. The results show that CNN + GP model is better than 18% of CNN alone in September and October (Table 2). It is verified again that CNN model with GP has practical value for corn yield estimation in New York state.

Table 2.
The MAPE of model performance, averaged from 2012 to 2021

	August		**September**		**October**	
	CNN	CNN+GP	CNN	CNN+GP	CNN	CNN+GP
MAPE	4.12	3.98	3.86	**3.26**	3.52	**2.98**

5. Conclusion

In this project, the deep learning model combined with remote sensing image data is used to predict the corn yield in New York State, which not only ensures the yield estimation accuracy, but also improves the yield estimation efficiency, and fills the gap in the research of regional yield prediction in New York state. The CNN model used in the study applies the dimensionality reduction concept in its convolution layer, maps all image bands to the histogram, and adds Gaussian process to weaken the estimation error caused by spatial correlation. The results show that the CNN model with Gaussian process is better than CNN alone in all aspects, and the error evaluation of MAPE is better than the prediction result reported by USDA by more than 12%. This study demonstrates the power of combining remote sensing data and deep learning technology, and also provides reference and technical support for using crop growth information with local agricultural departments to predict crop yield in advance and reflect the possible harvest changes caused by environmental impact in time.

6. Discussion

There are still some caveats in this project, which warrant future improvement.

(1) In this study, only the effects of temperature and solar radiation on corn crops are considered in the corn remote sensing yield estimation model, but some other important yield components such as precipitation, soil, crop management parameters and other variables are not considered. There is still a certain gap between the constructed model and the actual production process.

(2) The accuracy of corn yield estimation by the yield estimation model is also related to the extraction of corn distribution information. This paper only uses CDL to extract corn planting areas in New York State, which may have limited accuracy. Therefore, in future research, it is necessary to obtain more accurate crop spatial distribution, to make the crop yield estimation process more rigorous.

(3) In this project, only one CNN model is used to estimate the yield, and the model is improved on this basis. Therefore, only the difference of yield estimation accuracy before and after GP incorporation is compared. In the future, comparison with more yield estimation models can lead to more convincing conclusions.

(4) The spatial resolution of MODIS data selected in this project is relatively low, so it can only predict yield at the county level. In the future, field-scale yield prediction can be explored by using recent satellite missions such as Landsat 9 and Sentinel-2.

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