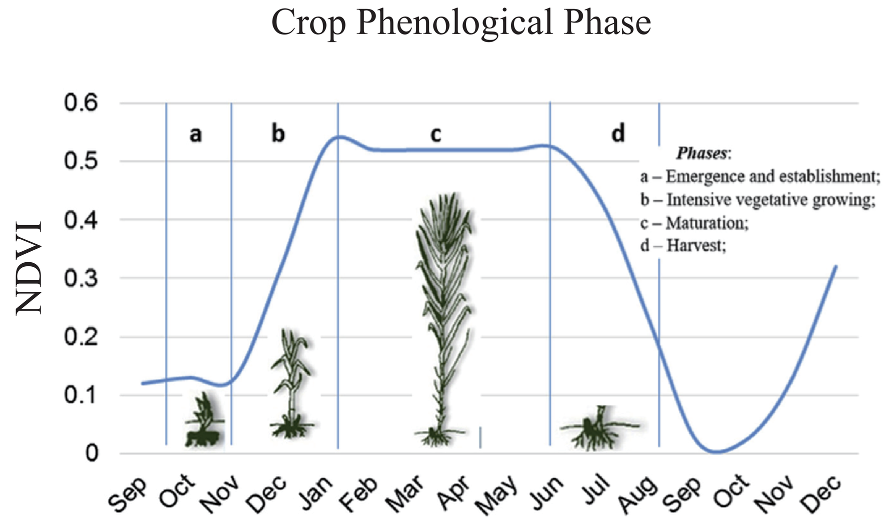
Generative-Discriminative Crop Type Identification using Satellite Images

Nan Qiao[1], Yi Zhao[1], Ruei-Sung Lin[1], Bo Gong[1], Zhongxiang Wu, Mei Han[1], Jiashu Liu

[1]Ping An Tech, US Research Lab

We proposed a machine learning model which combines generative and discriminative models and achieved averaged AP score of 0.903 over all tested crops and regions under the limitation of small dataset and label noise using satellite images taken at different times.

- We do crop type classification based on the fact that for most plants species, phenological event like emerged, mature, and harvested often occurs at a relatively stable time node over a long time period.
- Vegetation indices can capture crops phenological characteristic. One commonly used vegetation index is the Normalized Difference Vegetation Index (NDVI), which is derived from red band and near infrared band from satellite images.



DATASETS QUICK FACTS

Sentinel-2 satellite

10m spacial resolution

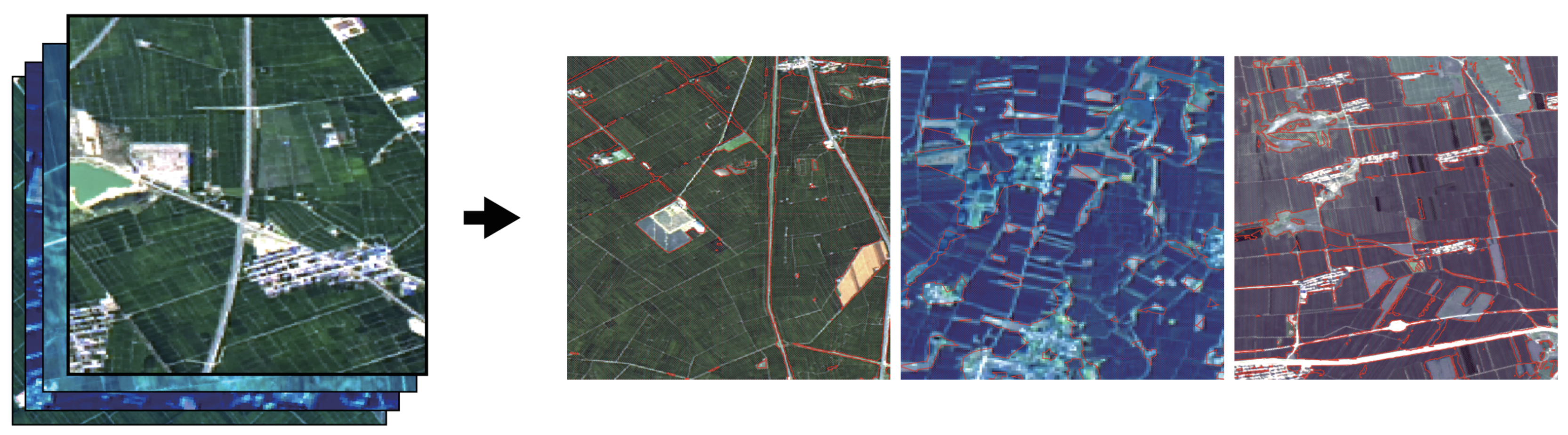
4 spectral bands: blue, green, red and near Infrared

3 or 4 time-nodes satellite images are used to identify a certain crop

Pixel-level crop type annotation

3 types of crop: rice, maize, winter wheat

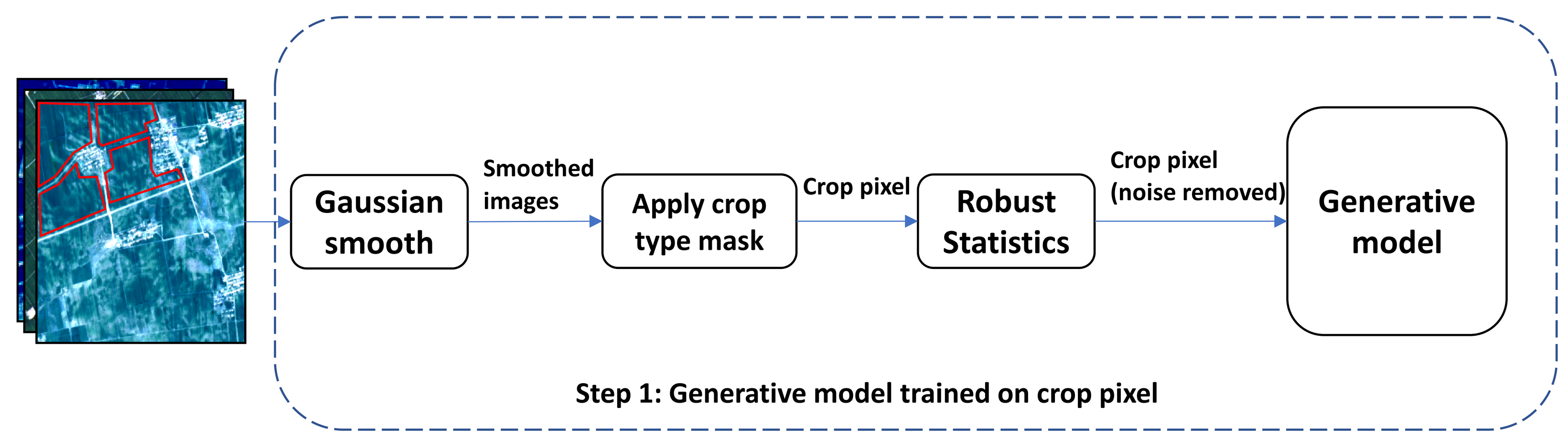
5 study regions in north-east, central and south of China, total 4800km^2

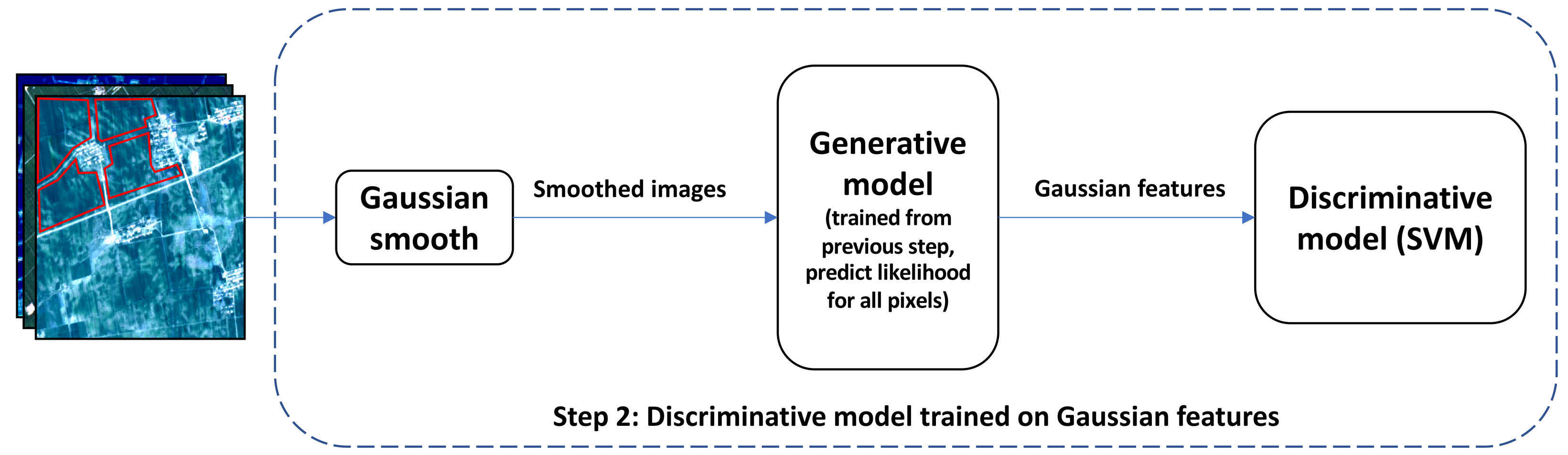


The proposed approach identifies crop types in pixel-level using multi-temporal satellite images. We implement this approach to 3 types of staple crop: rice, winter wheat, and maize. From left to right: satellite images taken at different times, examples of identification results of rice, wheat, and maize (marked by red shadow).

METHOD

1. Gaussian smooth to eliminate noise in satellite images.
2. Remove outliers using robust statistics to eliminate false-positive mislabels in annotation map.
3. Generative part: for each band (as well as NDVI), a multi-variate Gaussian distribution is estimated over all time nodes using crop area pixels. Convert spectrum images to likelyhood maps calculated by these distributions.
4. Discriminative part: train a support vector machine (SVM) classifier using likelyhood maps as features and crop type annotation map as labels.



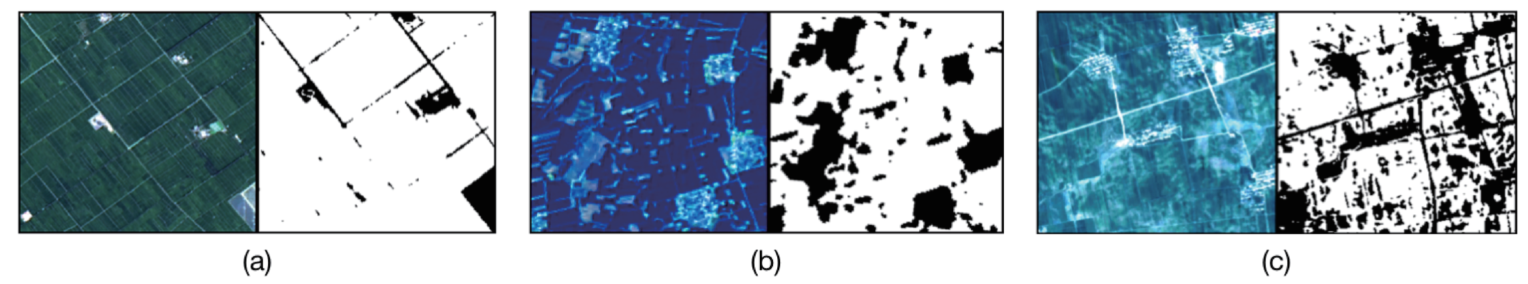


Flowchart of Generative-Discriminative model. Part1: Fit generative models with time-series crop area spectrum values. Part2: Train an SVM classifier based on Gaussian features calculated from stack images using the generative model.

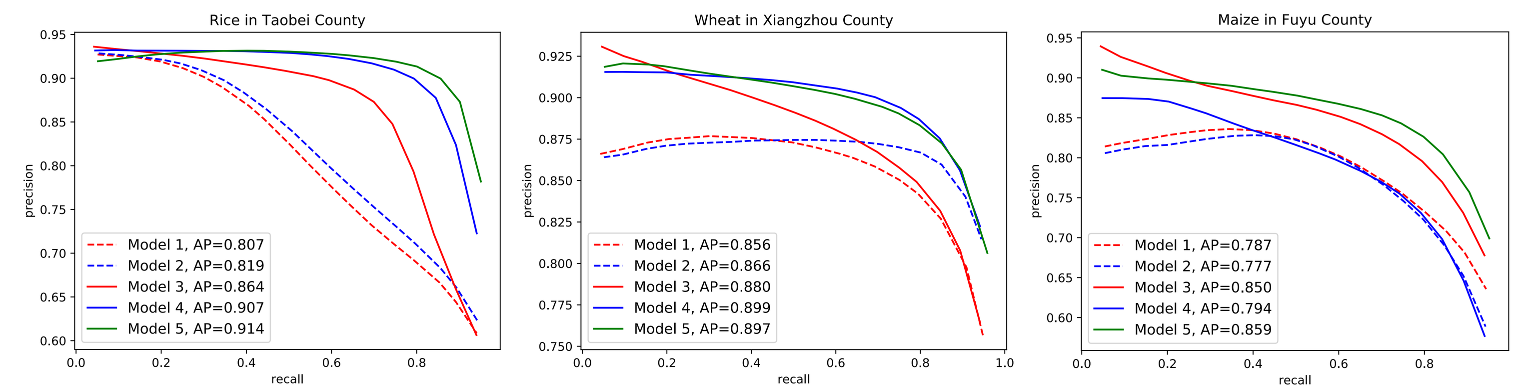
RESULTS

Dataset Description

Crop type/Region	Phenology(month)	Image size
Rice/Taobei, Jilin	May/Aug/Sept	3000×2000
Wheat/Xiangzhou, Hubei	Oct/Dec/Mar	2500×2000
Maize/Fuyu, Heilongjiang	May/Jul/Sept	2900×2100
Wheat/Suiyang, Henan	Oct/Nov/Dec	5000×4000
Wheat/Yuanyang, Henan	Dec/Mar	7600×3400



Identification result examples of three crop models. Left to right: (a) rice in Taobei County, (b) wheat in Xiangzhou County, and (c) maize in Fuyu County. In each case, left images are satellite image with RGB channels, right images are identification result, in which white and black colors represent crop area and non-crop area respectively.



Model Description

#	Input	Method
1	NDVI bands over all time nodes	Multivariate Gaussian dist. over all bands
2	NDVI bands over all time nodes	Product of 1d Gaussian dist. on each band
3	all bands over all time nodes	Multivariate Gaussian dist. over all bands
4	all bands over all time nodes	Product of 1d Gaussian dist. on each band
5	Gaussian features	SVM on Gaussian features

Precision-recall curves of three crop types (left to right: rice, wheat, maize). Models using all bands as input (solid-line curves) are always better than those using only NDVI band (dash-line curves). No generative model dominates in all testing areas. Gaussian features + SVM (green line) always gives relatively better and more

FUTURE WORK

- Apply the model on other crops, for instance, soybean, tobacco and oilseed rape, as a general identification model.
- Improve model's geographical generalization ability.

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