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THE MONITORING OF NON-FARMING AND NON-GRAIN PURPOSES IN ARABLE LAND OF ZHEJIANG, CHINA WITH DOMESTIC SATELLITE IMAGERY

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ABSTRACT:

Arable land protection is essential for Zero hunger the Sustainable Development Goals of United Nations, and the arable land protection includes two aspects, non-farming and non-grain. We try to monitor the arable land protection in Zhejiang with domestic satellite imagery. Satellite remote technology has become an essential way to monitor the land cover change (for non-farming) and grain crops (for non-grain). However, current monitoring frequency and scale were unable to satisfy the needs for non-farming monitoring. The low-resolution image cannot satisfy the feature of land fragmentation of Zhejiang for non-grain monitoring. To address the above problem, this paper proposes a land cover change method to monitor non-farming purposes based on deeplabv3+ with monthly coverage 2 meters resolution images. By focusing on rebuilding training data set and improving training strategy with hard example training, the difficulty of the spurious change caused by the adjustment of farming structure is solved. At the same time, this paper builds three training processes (Initial training, Fine training, Retraining for promotion) based on Fully Convolutional Neural Network FCN-8S to monitor the main grain crops in Zhejiang. The phenological features are added into the process of training to further improve the accuracy. At present, land cover change method of this paper has been applied in Zhejiang province and the monitoring of grain crops has been carried out in some regions according to the specific requirements. The result shows that both the two methods exhibit good accuracy and generalization ability at the time and space scale.

1. INTRODUCTION

Zero hunger is component of Sustainable Development Goals of United Nations and arable land protection is essential for achieving zero hunger. We try to monitor the arable land protection in Zhejiang with domestic satellite imagery because of the ability of high resolution and monthly coverage. The monitoring of arable land protection includes two aspects, the monitoring of non-farming and the monitoring of non-grain. Non-farming means some human activities to destroy the structure of arable land. Non-grain mainly refers to the fact that no grain but cash crops are grown on the arable land.

For the monitoring of non-farming, satellite remote sensing technology has become an indispensable way to capture the human activities from the perspective of land cover change (Omar et al., 2020; Nguyen et al., 2020). Lots of studies concentrate on the change in macro level with low and medium-resolution images (Keil et al., 2015; Saurabh et al., 2020; Chen et al., 2021), or in straightforward, they observed a large area of arable land transformed into forest, buildings, etc. However, non-farming monitoring is interested in the occupation in micro level with high-resolution images, or in straightforward, we need to observe some small area of human activities like newly-established building, excavation, etc in arable land (Minimum area:100 square meters). Therefore, current researches cannot satisfy non-farming monitoring in the spatial scale. The studies now concentrate on the annual monitoring (Renzon et al., 2018; Krina et al., 2020; Qu et al., 2020), we consider that the time scale is another problem to meet the business needs of rapid and accurate detection of non-farming purposes. This research aims at developing a monitoring method based on deep learning to detect land cover change in arable land with monthly high-resolution domestic imagery for good generalization ability of time scale.

For the monitoring of non-grain, satellite remote sensing technology has become an indispensable way to monitor the categories of crops by spectral information. Numerous studies concentrate on sentinel or Landsat (Martin et al., 2012; Jun-De et al., 2018; Karakizi et al., 2021; Mla et al., 2021). However, land fragmentation is a typical feature of Zhejiang province, which means many arable lands with small areas exist. Therefore, current research based on sentinel or other medium-resolution images cannot be applied in Zhejiang. This research aims at developing a monitoring method based on Convolution Neural Network with higher-resolution domestic images for higher precision and better generalization ability to monitor staple grain crops including wheat, early season rice, late season rice, double late rice in Zhejiang.

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2. MATERIALS AND METHODS

2.1 Earth Observation System

After several years of continuous development, author's institute has established mature co-ordination mechanisms of high-resolution visible spectral remote sensing images in Zhejiang: (1) The images with 0.5 meters resolution cover the whole province every first half year, (2) The images with 0.8 meters resolution cover the whole province every second half year, (3) The images better than 2.5 meters resolution cover the province every month. Some of images are from Land Satellite Remote Sensing Application Center, MNR, while the others are from domestic commercial satellites. To meet the needs of rapid detection, the images better than 2.5 meters resolution have become the main source in this paper, which including ZY1-02C, CBERS-04A, etc. (Table 1).

Sensor Name	Spatial Resolution/meter	Revisit Period/day
ZY1-02C	2.36	3
CBERS-04A	2	5
ZY3-01	2.1	3-5
GF-1 B C D	2	4(sway)/41
GF-1	2	4(sway)/41
GF-2	0.8	5(sway)/69
GF-6	2	2
TH01	2	58
BJ-2	0.8	1

Table1. Some technical parameters of the satellite images

Remote sensing technology has became a new digitized mean widely used in government departments of Zhejiang, such as natural resources protection, ecosystem restoration, land spatial planning, economic benefit analysis, etc. This paper is one work of natural resources protection.

According to the information collected by the authors, in the future, on the one hand, we will strength the obtainment of Multi-sources images, such as Multispectral Image, Hyperspectral Image, InSAR, etc. On the other hand, we will strength the production of high-resolution remote sensing products, such as Vegetation Coverage, Night Light Development index, Land Coverage, etc.

2.2 Data and Study Area

The monitoring of non-farming and non-grain purpose is carried out within the scope of arable land, and the range is achieved by management department, so we do not need to extract by images.

According to the needs of rapid detection for non-farming monitoring and at the same time, the grain crops monitoring needs the images at a particular time phase meeting the requirements of phenology. Due to the facts that the acquisition time of the images with 0.5 meters and 0.8 meters will be lagged and uncertain, so the images better than 2.5m resolution including ZY1-02C, CBERS-04A, ZY3-01, GF-1 B C D, GF-1, GF-2, GF-6, TH01, BJ-2 were preferred. The difference is that we only use 3 band information (Red, Green, Blue) for the non-farming monitoring but 4 band information (Red, Green, Blue, NIR) for non-grain monitoring. In this paper, We choose some regions of different topographic features to show results of the methods. These regions distribute in different locations in Zhejiang, region 1 locates in the hills, region 2 locates in the plain, region 3 locates in mountainous areas, others locate by the sea.

2.3 Method of non-farming monitoring

The non-farming land cover change detection should be applied frequently for early detection over a vast area, so this paper uses deep learning method to improve the generalization ability. The policy points out that the types of non-farming land cover change include newly-established building, road, aquaculture pond and excavation. These land cover changes consist of training samples (including pre change image, post change image and labels), we used deeplabv3+ to train these data and obtain a good fitting result, but the accuracy of test result cannot be satisfied.

Through our analysis of the test result, three reason are considered to reduce the accuracy: (1) the newly-established agricultural film is really land cover change by image comparison intuitively but it does not belong to non-farming purpose, (2) the newly-established aquaculture pond belongs to non-farming purpose, the newly-established reservoir does not belong to non-farming purpose, and the two are difficult to distinguish, (3) because of the improvement of monitoring frequency, spurious changes caused by the adjustment of farming structure appear, such as duckweed in aquatic farming or some exposed arable lands.

We add these spurious changes into training data sets as negative samples, at the same time, we embed a concept about hard example training (Shrivastava et al., 2016; Chen et al., 2018) to improve the construction of training data set and the strategy of model training. Based on deeplabv3+, according to the test results (mainly by misjudgement and the loss), data sets are subdivided into hard positives and negatives, easy positives and negatives. In our implementation, we build a module for training hard examples absolutely to update the network weights for higher accuracy (Figure 1).

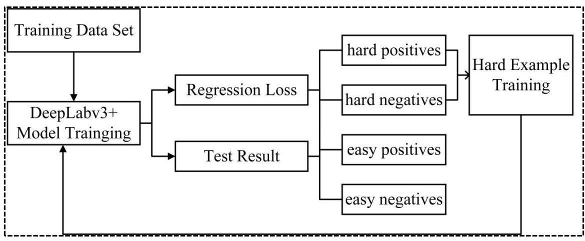


Figure1. Land cover change method with hard example training

2.4 Method of non-grain monitoring

The main grain crops in Zhejiang are early season rice, single late rice, double season rice and wheat. This paper determines the best observation period by phenological period and NDVI time sequence curve for monitoring them.

Three training processes are built based on Fully Convolutional Neural Network FCN-8S (Long J et al., 2015) for easy training data sets established and better generalization ability. (1) Initial training: The training data sets are gathered by the work of natural resources monitoring, according to the loss of fitting and the accuracy analysis, determine the appropriateness of the fit. (2) Fine training: we choose some typical areas and the training data sets are obtained by manual interpretation, on the basis of the Initial training. Consequently, the training parameters such as convolution kernel size, convolutional layers and deconvolution layers are fine-tuned further. (3) Retraining for promotion: we carry out cross-validation from both the time and space scales to improve the generalization ability (Figure 2).

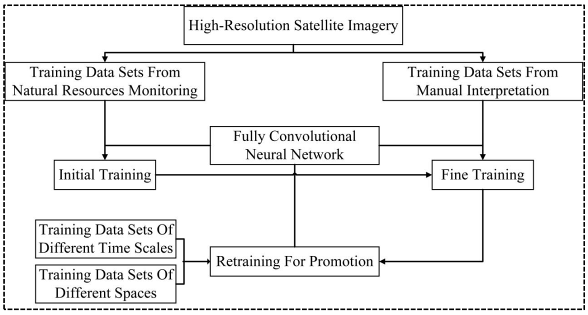


Figure2. Three training processes based on Convolutional Neural Network for grain crops monitoring

We add phenological features into the process of training to avoid that the artificial turf and nursery stock have the similar characteristics with grain crops (Figure 3).

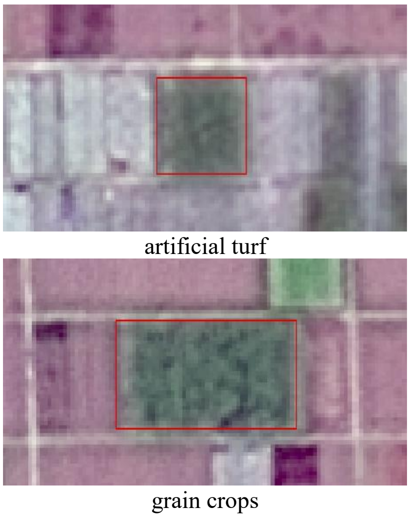


Figure 3. artificial turf and grain crops are difficult to distinguish in the image of one phase

3. RESULT AND DISCUSSIONS

3.1 The training data sets and training process of non-farming monitoring

We build training data sets with newly-established building, road, aquaculture pond, excavation, the important is that keep the quantity balance of each category, the fitting loss reaches stability when the data volume comes to 10000. The test result shows that the agricultural film, season alternation and reservoir are misjudged, so we added these into training data sets as negative samples which ratio to the positive samples is 1:1.

We repeat the training process, the result is irregular when the land cover category is excavation, season alternation, reservoir and aquaculture pond, which means the model is confusion owing to the feature of these samples is similar.

Finally, we build the data set of hard positives, hard negatives, easy positives and easy negatives for land cover change detection in arable land with about 20000 data volume. The hard positives include excavation and aquaculture pond, the hard negatives include season alternation and reservoir, the easy positives include road and building, the easy negatives include agricultural film, the number of each category is the same (Figure 4). Hard example model is a light-weighted model with fewer convolution layers. We gradually take up some number of hard examples for hard example training model and the rest is still participated in the training process in the main model. When the ratio is one-third, we get both best fitting loss and test accuracy (Table 2).

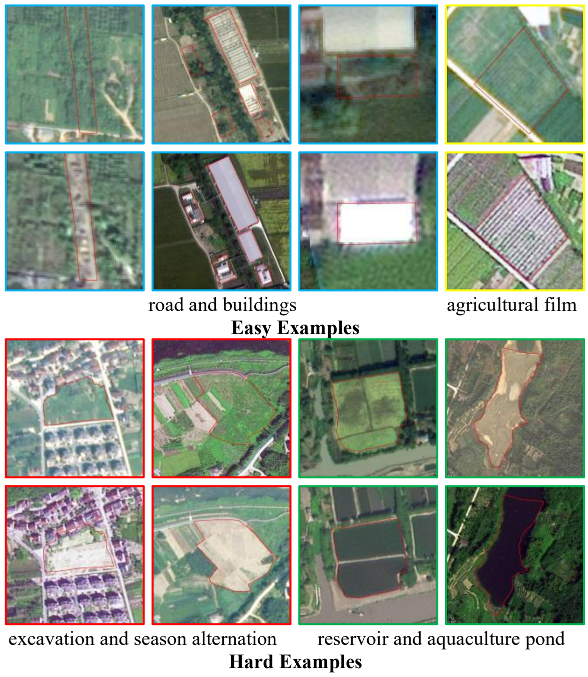


Figure 4. Typical examples of training sample

Training method	Loss	Accuracy
Model: deeplabv3+ Training sets: positives only	0.21	59.84%
Model: deeplabv3+ Training sets: positives and negatives	0.15	76.31%
Model: deeplabv3+ with hard training Training sets: easy and hard examples	0.03	92.34%

Table2. The improvement of loss and accuracy during the training processes

3.2 Suspected non-farming land cover change during whole year

Following the monitoring, we get the suspected non-farming land cover change in the selected regions frequently during the year of 2021 (Figure 5). According to the field survey, no land cover change in arable land is missed basically and the accuracy is higher than 85%. We also statistic the suspected land cover change accuracies of images with different months and different regions which are all higher than 85% (Table 3). It proves that the proposed method of this article has good generalization ability.

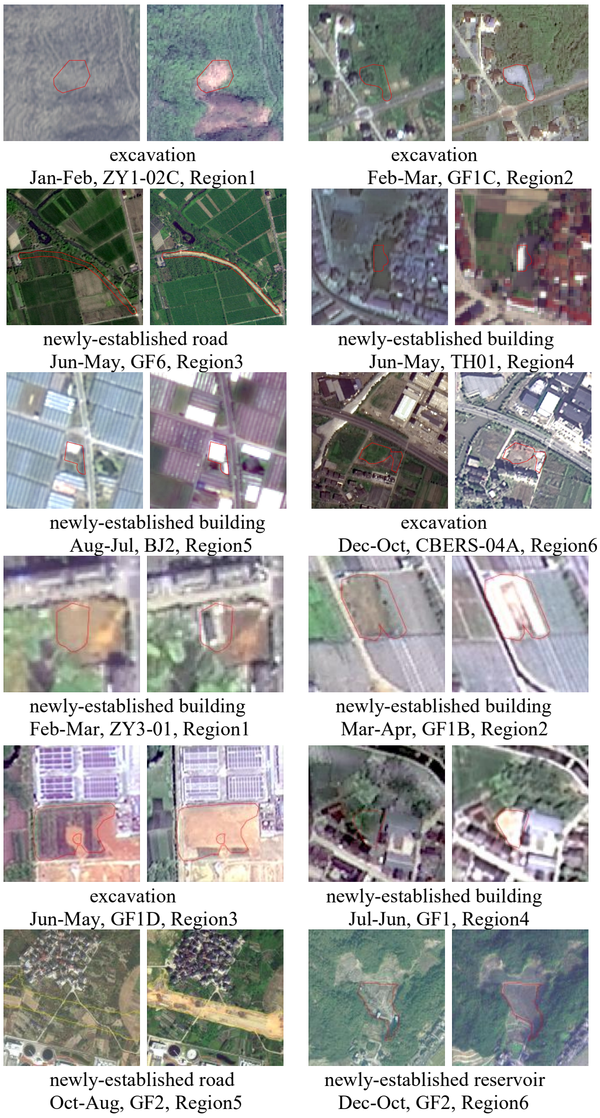


Figure5. Examples of suspected arable land cover change

Month	Number of monitoring	Number of exact	Accuracy
Jan-Feb	14	12	85.71%
Feb-Mar	13	12	92.30%
Mar-Apr	68	60	88.24%
Apr-May	79	70	88.61%
May-Jun	92	83	90.22%
Jun-Jul	81	73	90.12%
Jul-Aug	63	57	90.48%
Aug-Sep	48	43	89.58%
Sep-Oct	42	36	85.71%
Oct-Nov	91	84	91.30%
Nov-Dec	68	61	89.71%

Region	Number of monitoring	Number of exact	Accuracy
1	132	119	90.15%
2	114	100	87.72%
3	105	93	88.57%
4	101	87	86.14%
5	98	94	95.92%
6	109	98	89.91%

Table3. The accuracy of suspected arable land cover change of different months and different cities during 2021

3.3 Best observation period and phenological features of grain crops

We obtain the phenological information of different rice and wheat in Zhejiang from the agricultural sector (Table 4), and then we ensure the best observation period by NDVI time sequence curve (Figure 6).

Grain Crops	phenological information	
	sowing stage	maturation stage
wheat	November	May
early season rice	April	July
late season rice	Mar	September
double season rice	June	November

Table 4. The phenological information of different grain crops

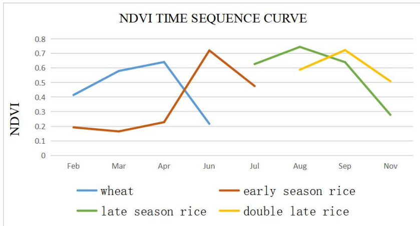
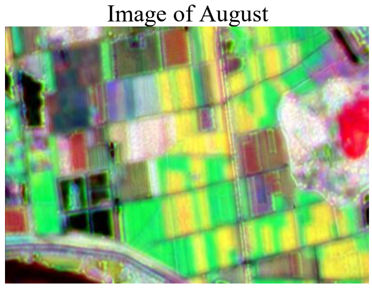


Figure 6. NDVI time sequence curve of grains in Zhejiang

The best observation period is decided by the maximum value of NDVI curve which means the target crop has the most obvious feature difference with other crops, the accuracy will be the best. According to Figure 6, the best observation period of wheat, early season rice, late season rice and double late rice are April, June, August, September respectively.

In the specific experiment, we find in the best observation period, artificial turf and nursery stock are existed which NDVI are also very high to be difficult to distinguish with target crops. The phenological feature (Figure 7), in other words, the D-value of NDVI is used in the process of training and finally the overall accuracy can be about 90%.

Image of August



D-value of NDVI by the image of June, August and October

Figure 7. The phenological feature is more prominent in the differences between grain crops and artificial turf (green: early season rice, yellow: artificial turf)

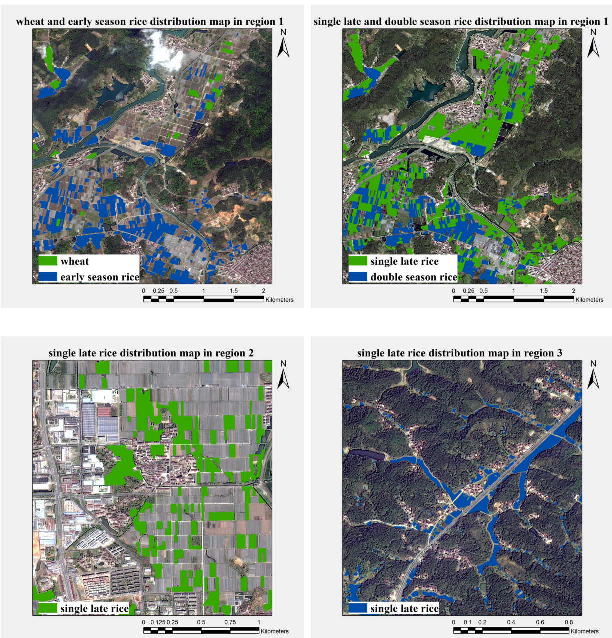
3.4 The monitoring result of grain crops

Sentinel-II is the commonly used data source for grain crops monitoring, we carry out the monitoring in the same area of Zhejiang both with GF-2 and sentinel-II images (Figure 8). The result shows that GF-2 has better overall accuracy, boundary precision and ability of extraction of arable land with small area because of higher spatial resolution. That improves the domestic satellite imagery is more suitable for the area like Zhejiang with the feature of land fragmentation.

GF-2 sentinel-II

Figure 8. Comparison of GF-2 and sentinel-II (the same scale)

We choose some regions by the work needs or major concerns to carry out grain crops monitoring test with the method of this paper(figure 9). Region 1 is located in hills of Zhejiang, its main grain crops are wheat, early season rice, single late rice and double late rice. Region 2 is located in plain of Zhejiang, its main grain crop is single late rice. Region 3 is located in mountainous area of Zhejiang, its main crop is single late rice. Region 4 is located by the sea, its main crops are wheat, early season rice, single late rice and double late rice. Region 5 & 6 are wheat planting demonstration areas of wheat. We evaluate the accuracy and the precision by the field survey and manual interpretation on pixel (Table 5). The result shows that the overall accuracy (OA) of wheat in different regions can up to 85%, and the overall accuracy (OA) of different rice in different regions more than 90%. As a result, the method has good generalization ability by the experiment with the imagery of greater range and different years.



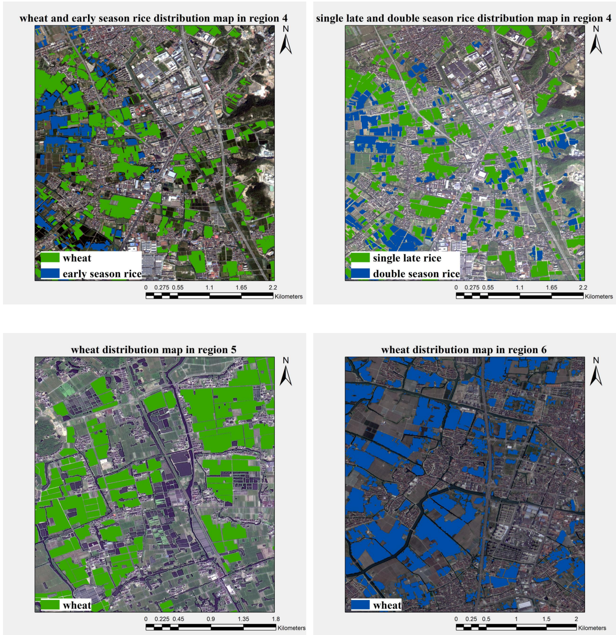


Figure 9. The Monitoring result of grains in different Regions

Region	Grain Crops	Omission	Error	Overall Accuracy
1	wheat	11.18%	3.74%	86.61%
	early season rice	5.70%	2.44%	92.03%
	single late rice	7.38%	1.46%	91.27%
	double season rice	4.47%	5.31%	90.41%
2	single late rice	5.07%	1.89%	93.15%
3	single late rice	5.84%	1.56%	92.70%
4	wheat	12.07%	2.03%	86.12%
	early season rice	5.21%	1.09%	93.72%
	single late rice	7.50%	0.81%	91.74%
	double season rice	5.45%	1.01%	93.66%
5	wheat	7.47%	3.20%	89.62%
6	wheat	13.38%	1.04%	85.73%

Table 5 Overall accuracy of grains monitor of figure 9 on pixel

4. CONCLUSION

This paper proposed an operational suspected non-farming land cover change detection method based on deep learning with domestic satellite imagery. We improve the construction of training data set and the strategy of model training for better generalization ability to take full advantage of frequency of monthly coverage. The method with remote sensing technology helps the management unit solve the problem that unable to monitor the suspected non-farming land cover change immediately and accurately.

This paper proposed a grain crops monitoring method based on Fully Convolutional Neural Network with domestic satellite imagery for the government of non-grain purpose. We build three training process including initial training, fine training, retraining for promotion to reduce the cost of training sample acquisition and improve the generalization ability. The method achieves good result in different regions and different grain crops. We also carry out comparison with GF-2 and sentinel-II, because of the improvement of spatial resolution, GF-2 has better result in the boundary and minutiae to suit the land fragmentation of Zhejiang.

The suspected non-farming land cover change has been provided to verify that the method is reliability and applicability. We continue to carry out non-farming monitoring in arable land in 2022, and up to now, we find the number of suspected non-farming land cover change is dramatically lower than the same period last year. It fully shows that the remote sensing as a new technology to participate in the natural resource protection can deter the occurrence of illegal human activities to destroy the arable land. Next, the method of grain crops monitoring will be promoted and applied in the whole province to governance non-grain purpose, and the non-farming purpose which has been found out will be retroactive verified with remote sensing images to determine the effect after governance.

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