A Statistical Study of Myanmar's Integrated Livestock-fish Production using Satellite Imagery

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Abstract

In recent years, integrated livestock-fish production is becoming increasingly popular in Myanmar. Economists hope to study this agricultural mode, however, thoroughly investigating it will be unrealistic. We seek to perform a statistical study with the help of satellite imagery and field investigation data. We formulate the problem as deep learning tasks, including object detection, object segmentation and cluster detection. The results have revealed several economical phenomenons that are worth studying, e.g. the continuous rise in the number of integrated farms and the clustering effect of farms in some regions.

1 Background

Myanmar is the largest country in mainland Southeast Asia, with China to its northeast and the Indian Ocean to its southwest. Myanmar is currently a developing country, and agriculture is one of the major components of its economy. The majority of the people in Myanmar are also farmers. The international society has been focusing on Myanmar on the problem of agriculture, food production, and poverty for a long time. Studies have been held to investigate the situations and give policy suggestions for the Myanmar government.

Recently, the military coup in Myanmar has caused many Chinese-funded companies and international organizations to leave Myanmar. As a result, the current situation in Myanmar is becoming less clear. On the other hand, some economic sanctions have restricted the trade of certain agricultural materials and products. COVID-19 also had a large impact on Myanmar. The exact influence of these factors remains unknown.

Since the current government no longer allows foreigners to perform investigations in Myanmar, it is impossible to obtain direct information via traditional survey approaches to answer the question above. Therefore, in this project, we propose an alternate solution: use deep learning approaches to investigate the agricultural status in Myanmar, with the help of satellite imagery and data from previous traditional investigations.

The project will mainly focus on a special agricultural mode in Myanmar, which is the integrated livestock-fish production. This agricultural mode was the target of a previous investigation led by the Peking University and the International Food Policy Research Institute (IFPRI). In 2018 and 2019, researchers have obtained first-hand data by visiting over 400 integrated farms. After the burst of COVID-19, the research team telephone-interviewed the farmers again for 5 rounds in total to keep updated on the farms' operating status. The data contains GPS locations, thus is easy to cooperate with satellite image data.

We hope that our deep learning-based method can reach relatively high performance and produce statistics to fill in the blank of first-hand data. Then the results will be carefully analyzed to form at least one policy report for the Myanmar government, at least one research paper for publication.

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Figure 1: The satellite image data. From left to right: (i) the entire cover range of the map, (ii) examples of chicken farms, (iii) an example of human annotations on the map of year 2018. The buildings in the red bounding boxes are chicken farms.

Furthermore, although we only focus on the integrated chicken-fish production in this study, our method has the potential to be applied to a variety of similar studies. Therefore, after finishing this study, we will eventually provide a deep learning-based reusable data pipeline.

2 Problem Definition

2.1 Data

In our work, we use two main sources of data: satellite imagery, and the data from the previous investigations in Myanmar.

Satellite imagery The satellite imagery that is used in this project is collected from an open-source global satellite image database. The database contains RGB images of different resolutions at different historical times. In our study, we mainly used the level-17 map (resolution 1 pixel $\approx$ 2 meters) for 8 years in total: 2010$\sim$2016 and 2018. We choose the 100km-radius circle range around Yangon, the largest city in Myanmar, as the range of our study. Our main targets are chicken farms and fish ponds in the satellite maps. Chicken farms are usually long, thin rectangle-shaped buildings and fish ponds are usually medium-sized, square-shaped water areas. The colors of the buildings are usually gray, brown, or blue, which indicates different farm types. Two main farm types are thatch and zinc/metal.

It is worth noticing however that the satellite image has several imperfections. First of all, the taken time of different images in a single year are not the same, which will harm our result. Secondly, level-17 maps are relatively low in resolution for the segmentation task. However, switching to level-18 is prohibitive due to image size. Therefore we download only a portion of the level-18 map for training segmentation models.

Investigation data the second source of data comes from a previous field survey. The GPS location of the farms that the researchers visited was recorded, along with their production scale and farm type information. However, the recorded GPS locations have biases, thus cannot serve as direct supervision. It can only be used as a verification for model performance.

The researchers also annotated around 3,500 chicken farms on the map of the year 2018 by human effort, which is all the farms in the range of our study. The annotations are in the type of bounding boxes, which can be used as ground-truth labels for training object detection models.

2.2 Formulation

To achieve the goals of our study, we must first formulate the statistical study into AI tasks. For studying the integrated livestock-fish production, the most critical factors include:

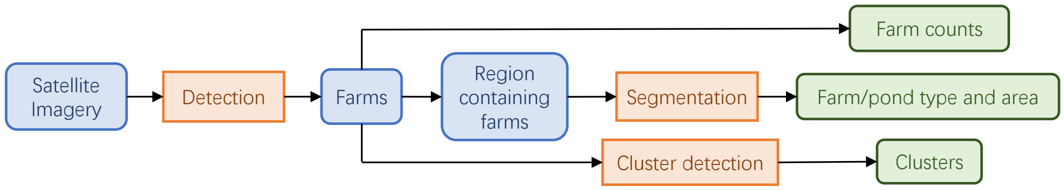

Figure 2: The overview of our entire model and the data pipeline. Starting from satellite images (blue), by applying detection, segmentation and cluster detection models (orange), we can extract desired information such as farm counts, farm size, farm type and clusters (green).

- **The total number of farms**, which most directly reflects the total amount of production. From previous investigations, researchers find that integrated farming starts getting popular in recent years. Therefore, the total number count should show a continuous increase.
- **The size and type of chicken farms**. Different sizes and types of chicken farms correspond to different production scales, which also indicate different wealthiness levels and farming strategies of farmers. For example, if the farmer wishes to operate the farm for a long period and he/she can afford the initial building fee, he/she will tend to use a zinc/metal structured farm, since it is more stable and requires less maintenance, although its construction cost is larger than a thatch farm.
- **The spatial-temporal distribution of farms**. This will reveal how the integrated farming mode spread across the country, and in which region locates most farms. The clustering effect is especially important.

Then, we focus on each sub-problem above respectively and provide solutions for each of them. The total number of farms can be directly formulated into an object detection problem. The size and type of each chicken farm correspond to segmentation and classification problems. Due to the difficulty of obtaining segmentation training data we consider both unsupervised and supervised methods. The spatial-temporal distribution of farms can be formulated into an unsupervised cluster detection problem.

3 Methods

In this section, we will introduce our methods for solving each sub-problem: chicken farm detection, unsupervised chicken farm segmentation, supervised segmentation, and cluster detection.

3.1 Chicken Farm Detection

Different from ordinary objects, chicken farms on a satellite map is harder to detect, since it has a small size, irregular appearance, and unbalanced spatial distribution. Therefore the model needs to be carefully designed based on these features. We adopt YOLOv4 [1], the state-of-the-art object detection model as our main backbone. It contains a feature pyramid structure, which is beneficial for small object detection. The inference speed of YOLOv4 is also very fast.

Since satellite images are very large, we cut large-scale satellite images into 608*608px sliding windows with overlaps. In post-processing, we eliminate repetitions via non-maximum suppression. To fit the small object size, we adjust the anchor size of the model to the average size of chicken farms, which can be solved by K-means clustering on hold-out examples. We also strengthened the data augmentation strategy of YOLOv4, including adding more rotation, flip and mosaic operations.

Since the true edge of a chicken farm can be hard to define, high IoU between the prediction and the label is not necessary. Therefore, we perform validation at different IoU thresholds. Concretely, we set the predictions whose IoU with the ground truth bounding box is larger than a certain threshold to be true positive predictions (and other predictions to be false positives), and compute the precision (P), recall (R), and the average precision (AP) under different thresholds.

3.2 Unsupervised chicken farm segmentation

To estimate the total production amount, it is important to calculate the total area of chicken farms, which leads to chicken farm segmentation. Since segmentation masks are usually hard to get, we propose an unsupervised segmentation method.

We adopt the Canny edge detector, a traditional computer vision method that extracts edges from an image. Concretely, it calculates the gradient map of the image, then performs non-maximum suppression and hysteresis thresholding. Since most chicken farms have rectangular shapes, we can extract the chicken farm area based on the detected edges.

Specifically, we start from bounding box predictions by the object detection model. We apply the Canny detector to the image patch inside the bounding box. Then we perform erosion and dilation to reduce noise and ensure continuity of edges. Finally, we extract the chicken farm area using rules: the farm must be a closed contour located near the center of the bounding box, and the contour should not contain ≥ 2 corners and the bounding box.

3.3 Supervised chicken farm segmentation and classification

Although the Canny edge detector can already perform approximate segmentation, it can be restricted by the light condition, the color of farms, and the quality of bounding boxes. Moreover, it cannot classify different types of farms; nor can they be applied to fish pond segmentation. To this end, we propose a supervised segmentation model, which has higher precision than the unsupervised model and is also more robust, versatile, and reusable.

We adopt U-net [2] as our backbone, a widely-used segmentation model. We additionally annotated a portion of images for labels. This includes 569 level-18 maps of size 200*200px containing at least one chicken farm and 109 level-17 maps of size 400*400px containing at least one fish pond. We divide chicken farms into two main categories, zinc and thatch, based on the material of their rooftops. The two categories can be divided by color.

We use ResNet34 [3] as the backbone. Similar to the object detection model, we use a strong data augmentation strategy. In the inference phase, we will use a similar-sized region containing the bounding box prediction as the input to the model.

3.4 Cluster detection

The goal of this subproblem is to describe the spatio-temporal distribution of farms and find large clusters. Since no annotation is available and the distribution of farms is sparse (1000$\sim$4000 farms in total in the 100km-radius circle), machine learning does not fit this task. We find that a distance threshold-based approach turns out to be effective.

Concretely, we perform tree searches starting at every detected farm. If there exist neighboring farms within a distance threshold, they are marked as the same cluster. Finally, we describe clusters by the convex hull of the farms within.

4 Results

4.1 Farm Detection and Count

We use the labeled maps in 2018 and split them into 8:1:1 for training, validation, and test. The test performance of the model under IoU threshold 0, 0.2, and 0.5 are shown in Tab. 1. The precision at IoU threshold 0 and 0.2 are over 86%, which is close to human performance. Though the threshold is low, in experiments we find that the bounding box has even higher quality than the labels. The reason for low IoU might instead be that the labels are imperfect.

Visualization of the detection results are shown in Fig. 3. As shown, the model is capable of detecting chicken farms in different terrains. The model can also distinguish between chicken farms and land buildings although they are similar in appearance. We record the total count of chicken farms under IoU threshold 0.2 in Tab. 3. We can observe a continuous increase, which is consistent with the investigation.

IoU threshold	Precision	Recall	mAP
0	0.872	0.866	0.872
0.2	0.866	0.860	0.851
0.5	0.655	0.656	0.517

Table 1: Performance of the detection model.

	Water	Thatch farm	Zinc farm
IoU (%)	88.3	83.0	82.7

Table 2: The performance of the supervised segmentation model.

Year	2010	2011	2012	2013	2014	2015	2016
Count	1239	1401	1568	1874	2571	2750	3814

Table 3: The total chicken farm count by the detection model.

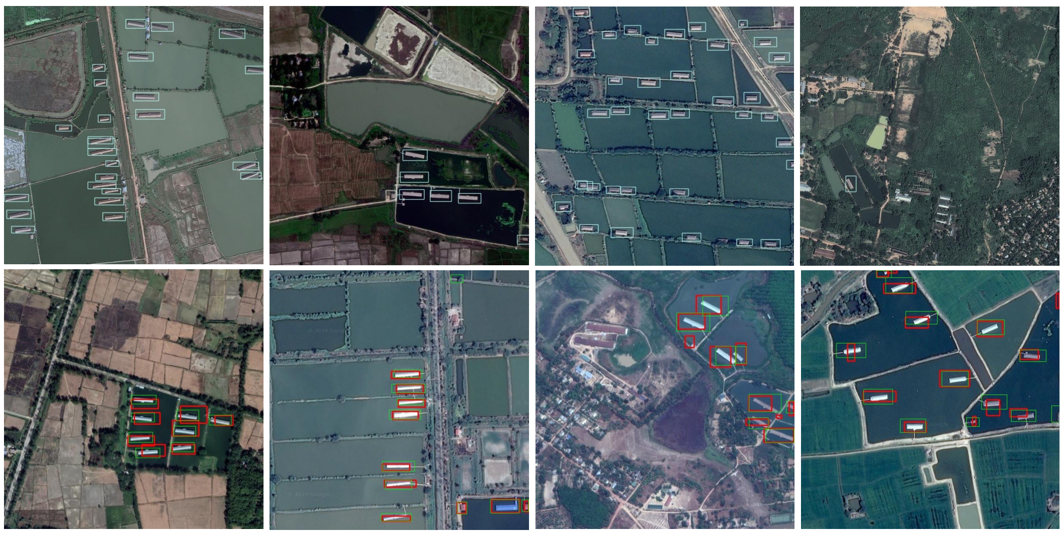

Figure 3: Visualization of the detection model. The first row: prediction results on year 2010. The bounding box predictions are marked in pale blue. The second row: prediction results on the test set of year 2018. The predictions are marked in green, and the annotation boxes are marked in red.

4.2 Farm/Pond Area Segmentation and Farm Type Classification

Canny edge detector A visualization of the Canny edge detector is shown in Fig. 4. As shown, the detector can basically capture the edges of the chicken farms, however there are still flaws, e.g. the third example in the figure.

U-net segmentation and classification We split the data into the training set and the validation set by 8:2 ratio. The validation IoU of the U-net model is shown in Tab. 2. The IoU is over 80%,

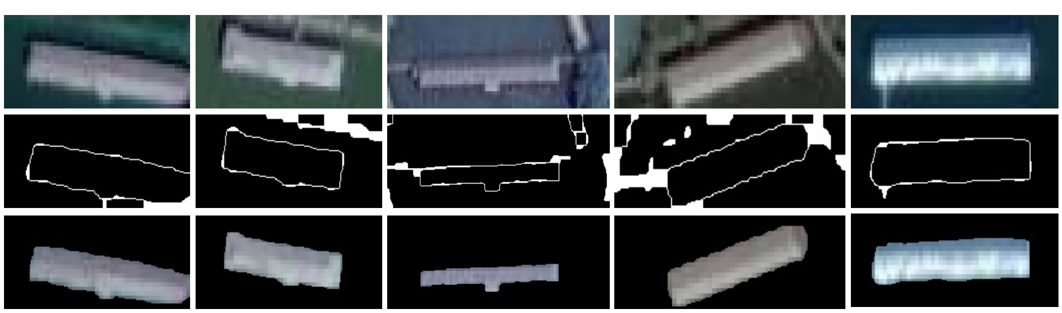

Figure 4: Visualization of the Canny edge detector. The first row: original bounding boxes. The second row: the binary edge map after Canny and erosion-dilation. The third row: the extracted chicken farm area.

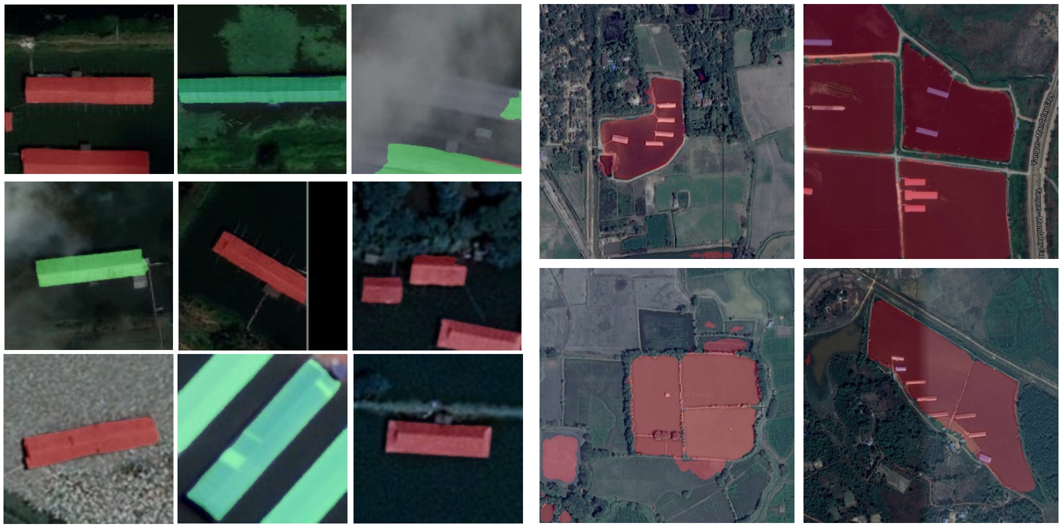

Figure 5: Visualization of the U-net model on the validation set. Left: chicken farm segmentation and type classification. Zinc/metal farms are colored in green and thatch farms are colored in red. Right: fish pond segmentation. Pond areas are colored in red.

which is very high given the limited amount of labeled data. A visualization is given in Fig. 5. In this visualization, we see the segmentation map predictions are very precise. The model only fails in extreme cases, e.g. heavy occlusion by clouds. For both farm and pond segmentation, when several targets are close, they will all be segmented out, while only one target on the center is desired. When performing global area calculation, we can eliminate repetitions by non-max suppression.

4.3 Cluster detection

The detection result of clusters (take the year 2016 as an example) is shown in Fig. 6. The largest cluster contains over 140 chicken farms. The clusters show some specific spatial distribution, which is related to the administrative division of Myanmar. We record each cluster's geographic coordinates and compare clusters within years, which results in novel discoveries. In the figure, we show an unusual shrink happened to one of the largest clusters.

5 Significance

Our method and result show significance in many aspects: for this specific study, for Myanmar, and for the field of social science research.

For this study, our model reaches a high performance that is comparable with human level. With more data and higher-resolution maps, this performance can even be further improved. We can now basically achieve the predefined goal. Furthermore, some discoveries are inspiring and can potentially lead to more relative research topics.

For Myanmar, since the government's agricultural statistics system is very undeveloped, our results have made contributions to this system. Our work can also reveal the importance of this integrated chicken-fish production mode for the food safety of Myanmar.

We point out that this integrated farming mode is beneficial in many aspects, including reducing economic risks for producers, utilizing land efficiently, and facilitating the reuse of excessive nutrients from livestock production. There are questioning voices about the pollution problem, however, this can be controlled by government regulations, e.g. by managing discharge of eutrophic water and mandating antibiotic withdrawals before harvest. Our work will offer statistical support for policy-makers. This will eventually be beneficial for improving Myanmar's food security and promoting sustainable development.

For the social science research field, our work provides a novel attempt that uses deep learning as research tools. In our work, AI and deep learning have shown many advantages over traditional

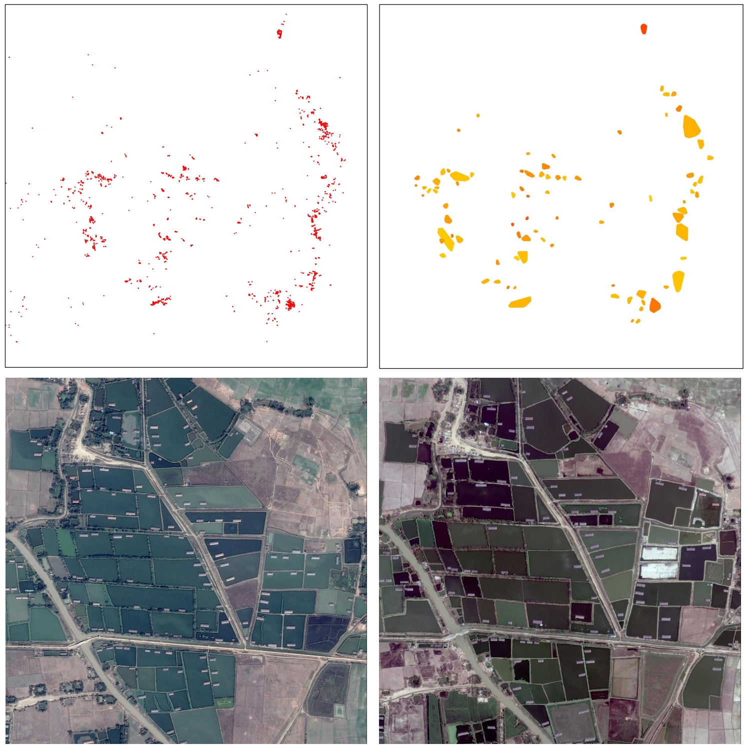

Figure 6: Visualization of the cluster detection model. Upper left: the distribution of single chicken farms. Upper right: the distribution of detected clusters. The minimum size threshold is 3 and the distance threshold is 500 meters. Clusters of lower density are colored in yellow, and clusters of higher density are colored in red. Lower left and right: the same cluster in the years 2016 and 2018.

approaches, including reducing human effort, broadening the research scope, and being more flexible and reusable.

6 Related Work

Integrated farming The researchers have been studying integrated farming in Myanmar since 2018. The primary results can be seen in survey notes [4] and publications [5, 6]. This can serve as a background and reference for our work.

Deep learning on Satellite Imagery Deep learning models based on satellite imagery have already been applied to a variety of tasks, including traffic supervision, weather report, etc. A recent work applies segmentation models to satellite images of West Africa to detect the total amount and area of trees [7]. This setting is very similar to ours. Currently, deep learning on satellite imagery is gradually raising more attention and has the trend to form an independent research direction. Learning from satellite images usually involves detecting small and scattering objects. Some previous works have proposed useful tricks to tackle these problems [8, 9].

Remote sensing Our work is also related to the remote sensing field. Different from RGB satellite imagery, remote sensing requires multi-modal satellite sensing data, e.g. visible light maps + infrared maps [10, 11]. It is often used for geographic measurements, e.g. extracting water area, extracting city area. The most famous method for water detection is the Normalized Difference Water Index (NDWI), however, it requires infrared maps, thus does not fit our task.

7 Conclusion

In this work, we combine deep learning with social science study. Specifically, we give a statistical study on the integrated livestock-fish production mode in Myanmar using satellite imagery. Under the current situation that most traditional researches are interrupted by the military coup and COVID-19, our work provides a novel perspective. Eventually, our results will benefit policymakers and the vast farmers in Myanmar.

We formulated the goal of our study into several AI tasks and designed solutions for each sub-problem. Despite that some of our model designs are task-specific, the main backbone of our model can be adapted to other data sources with only a little modification. Therefore, our methods have the potential to be applied to a wide range of similar studies. We hope that in the future, we can construct a complete AI system for social science. With such a system, the scope for social science researches will be greatly broadened.

Until now, the main technical part of this study is finished, but there are still some future works ahead. On one hand, we are collecting higher-quality satellite maps to increase the precision of the models. On the other hand, we still need further investigation to verify our discoveries and finally reach a conclusion.

References

[1] Alexey Bochkovskiy, Chien-Yao Wang, and Hong-Yuan Mark Liao. Yolov4: Optimal speed and accuracy of object detection. *arXiv preprint arXiv:2004.10934*, 2020.

[2] Olaf Ronneberger, Philipp Fischer, and Thomas Brox. U-net: Convolutional networks for biomedical image segmentation. In *International Conference on Medical image computing and computer-assisted intervention*, pages 234–241. Springer, 2015.

[3] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 770–778, 2016.

[4] Peixun Fang, Ben Belton, Hnin Ei Win, and Xiaobo Zhang. Monitoring the impact of covid-19 in myanmar: Yangon peri-urban poultry farmers - november 2020 survey round. *Myanmar SSP Policy Note 42. Washington, DC: International Food Policy Research Institute (IFPRI)*, 2020.

[5] Peixun Fang, Ben Belton, Xiaobo Zhang, and Hnin Ei Win. Monitoring the impact of covid-19 in myanmar: Yangon peri-urban poultry farmers - november 2020 survey round. *Myanmar SSP Policy Note. Washington, DC: International Food Policy Research Institute (IFPRI)*, 190, 2021.

[6] Ben Belton, Myat Thida Win, Xiaobo Zhang, and Mateusz Filipski. The rapid rise of agricultural mechanization in myanmar. *Food Policy*, 101:102095, 2021.

[7] Martin Brandt, Compton J. Tucker, Ankit Kariryaa, Kjeld Rasmussen, Christin Abel, Jennifer Small, Jerome Chave, Laura Vang Rasmussen, Pierre Hiernaux, Abdoul Aziz Diouf, Laurent Kergoat, Ole Mertz, Christian Igel, Fabian Gieseke, Johannes Schöning, Sizhuo Li, Katherine Melocik, Jesse Meyer, Scott Sinno, Eric Romero, Erin Glennie, Amandine Montagu, Morgane Dendoncker, and Rasmus Fensholt. An unexpectedly large count of trees in the west african sahara and sahel. *Nature*, 587(7832):78–82, Nov 2020.

[8] Adam Van Etten. You only look twice: Rapid multi-scale object detection in satellite imagery. *arXiv preprint arXiv:1805.09512*, 2018.

[9] Adam Van Etten. Satellite imagery multiscale rapid detection with windowed networks. In *2019 IEEE Winter Conference on Applications of Computer Vision (WACV)*, pages 735–743. IEEE, 2019.

[10] Liwei Li, Zhi Yan, Qian Shen, Gang Cheng, Lianru Gao, and Bing Zhang. Water body extraction from very high spatial resolution remote sensing data based on fully convolutional networks. *Remote Sensing*, 11(10), 2019.

[11] Yongfa You, Siyuan Wang, Yuanxu Ma, Guangsheng Chen, Bin Wang, Ming Shen, and Weihua Liu. Building detection from vhr remote sensing imagery based on the morphological building index. *Remote Sensing*, 10(8), 2018.