# In-Domain Self-Supervised Learning Can Lead to Improvements in Remote Sensing Image Classification

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#### **Abstract**

Self-supervised learning (SSL) has emerged as a promising approach for remote sensing image classification due to its ability to leverage large amounts of unlabeled data. In contrast to traditional supervised learning, SSL aims to learn representations of data without the need for explicit labels. This is achieved by formulating auxiliary tasks that can be used to create pseudo-labels for the unlabeled data and learn pre-trained models. The pre-trained models can then be fine-tuned on downstream tasks such as remote sensing image scene classification. The paper analyzes the effectiveness of SSL pre-training using Million AID - a large unlabeled remote sensing dataset on various remote sensing image scene classification datasets as downstream tasks. More specifically, we evaluate the effectiveness of SSL pre-training using the iBOT framework coupled with Vision transformers (ViT) in contrast to supervised pre-training of ViT using the ImageNet dataset. The comprehensive experimental work across 14 datasets with diverse properties reveals that in-domain SSL leads to improved predictive performance of models compared to the supervised counterparts.

Keywords: Remote Sensing, Self-Supervised Learning, Earth Observation, Deep Learning

# 1 Introduction

The growth in remote sensing data availability is only matched by the growth and developments in the area of artificial intelligence (AI), and in particular in the field of computer vision. More specifically, recent trends in deep learning have led to a new era of image analysis and raised the predictive performance bar in many application domains, including remote sensing and Earth Observation (EO) [4]. Deep models can leverage these large amounts of data, in turn, achieve state-of-the-art performance in various EO tasks (incl. land use/land cover classification, crop type prediction) using large quantities of labeled (ground truth) remote sensing data (typically hundreds of thousands of labeled images).

However, for many highly relevant tasks (e.g., archaeological sites identification, pasture grazing, fertilization in agriculture), there is lack of data which is (sufficiently) large, publicly available, and more importantly - labeled. This is a limiting factor in the further uptake and use of AI for remote sensed data. On the one hand, this is expected and understandable, considering that large-scale dataset annotation is an expensive, tedious, time-consuming, and largely manual process. On the

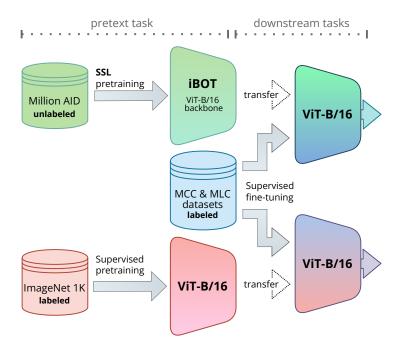


Figure 1: Illustration of the experimental pipeline used to test our research hypothesis: Whether in-domain self-supervised learning can lead to improvements in the performance of remote sensing image scene classification models. The learned models using self-supervised (iBOT) or supervised (ViT) learning are transferred to the downstream tasks of image classification by fine-tuning of the weights. We assess the predictive performance of the resulting fine-tuned models.

other hand, such scenarios call for methods that can learn and represent the (visual) information given in the images without needing labeled examples. Such methods are developed using the SSL paradigm [16].

SSL provides a novel approach to the challenge of data labeling by leveraging the power of unlabeled data without the added overhead of manual annotation. In the SSL paradigm, a model is learned in two stages: self-supervised training is first performed on a large unlabeled dataset, and then the trained model is transferred to specific downstream tasks with limited amount of labeled data. In the context of remote sensing, the downstream tasks, also known as target tasks can be scene classification, semantic segmentation, representation learning and object detection [16].

The main idea behind SSL is to create auxiliary pretext task for the model from the input data itself. While solving the auxiliary task, the model learns useful representations and relevant features of the input data and its underlying structure that can be used for downstream tasks. There are various types of pretext tasks such as augmentation of the input data and then training a network to learn the applied augmentation, for example rotation, color removal, repositioning/removing patches in the images. In this way, the learned representations can help to bridge the gap in performance between balanced and imbalanced datasets [10].

In this work, we investigate the following research hypothesis: Whether in-domain self-supervised learning can lead to improvements in the performance of remote sensing image scene classification models. The downstream task is thus image scene classification. In a typical scenario, working with large scale EO images, this task addresses classifying smaller image (patches) extracted from the much larger remote sensing image. The extracted images can be then annotated with a single or multiple annotations based on the content using explicit semantic classes (eg. forests, residential area, rivers etc.). Given an image as an input, the model needs to output a single or multiple semantic labels, denoting land-use and/or land-cover (LULC) classes present in that image.

The research hypothesis is tested through a series of experiments across 14 remote sensing image datasets from the downstream task. As an architecture for SSL pre-training we use the iBOT frame-

work [19] with Vision Transformer (ViT) [6] as a backbone model. Such architecture has not been explored in the context of SSL from remote sensing imagery.

The SSL paradigm has been previously exploited in the context of remote sensing image scene classification. For example in [13], a multi-augmentation contrastive learning method (SeCo) is proposed to take into account the seasonal changes in the satellite data. In [17], a large-scale unlabeled dataset for SSL in Earth observation (SSL4EO-S12) is presented and evaluated using several SSL algorithms, such as MoCo [8], DINO [2] and MAE [7]. In [15], a rotated varied-size window attention method is explored to advance the performance of plain ViT. Using MAE as a SSL pretraining method, the proposed approach is evaluated on few downstream tasks for remote sensing image scene classification. In [1], a large-scale multitask dataset (Satlas) for benchmarking and improving remote sensing image understanding models is presented and analyzed using MoCo and SeCo as SSL methods.

Whilst it is evident that SSL for remote sensing images is getting increased attention by the researchers and practitioners, there are several limitations preventing even more increased uptake by the community. Our study aims to address the limitations in the existing body of work by making the following contributions:

- A comprehensive experimental evaluation across a large number of diverse datasets we use 14 remote sensing image scene classification datasets with different number of images (ranging from  $\sim 2K$  to  $\sim 500K$ ), number of labels per image (from 2 to 60), different spatial resolution, size and format, and varying label distribution (perfectly balanced datasets as well as highly imbalanced datasets);
- Clearly defined protocols for standardization of the experimental work and reproduction of the results; and
- Standardization of the splits of the data into train, validation and test parts thus making the comparison of the results from different studies easier.

In the reminder, we first explain in more details the iBOT self-supervised method and introduce the remote sensing image scene classification as a downstream task to evaluate the performance of the pre-trained models. Next, we explain the experimental design of the study, including the implementation details and settings. Lastly, we present and discuss the experimental results and provide guidelines for further work.

#### 2 Methods and materials

The computer vision research community has developed a variety of SSL methods based on different deep learning architectures, including autoencoders, generative adversarial networks, contrastive methods based on negative sampling, knowledge distillation and redundancy reduction. A recent overview of SSL methods in remote sensing [16] reports that the iBOT method [19] achieves highest top-1 accuracy on the ImageNet dataset – this is why we selected this method to test our hypothesis.

#### 2.1 Self-supervised pre-training using iBOT

The iBOT (image BERT pre-training with Online Tokenizer) model architecture [19] has exhibited exceptional performance in SSL tasks [16], establishing it as a state-of-the-art solution. Inspired by Masked Language Models (MLM) [3], which involve randomly masking and reconstructing a set of input tokens, the iBOT model has become the de facto standard in language-related tasks. At the core of MLM lies the lingual tokenizer, responsible for segmenting sentences into semantically meaningful tokens.

Building upon the success of MLM, the iBOT model extends its effectiveness to vision tasks through Masked Image Modeling (MIM), offering improved training pipelines for Vision Transformers. However, a significant challenge arises in visual tasks due to the absence of statistical analysis of word frequency as seen in language tasks. In this regard, MIM aims to design a visual tokenizer capable of accommodating the continuous nature of images.

MIM is based on the concept of knowledge distillation, and extracts knowledge from the tokenizer and engages in self-distillation with a twin teacher acting as an online tokenizer. In this setup, the

target network receives the masked image as input, while the online tokenizer processes the original (unchanged) image. The objective of this approach is for the target network to learn the process of correctly recovering each masked patch token, aligning it with the corresponding output from the tokenizer.

#### 2.2 Unlabeled dataset for the self-supervised pretext task

At the core of the definition of the self-supervised pretext task lies the selection of the unlabeled data used to learn the image representations. In our study, we utilize the Million Aerial Image Dataset (MillionAID) [12] dataset with remote sensing scene images, which adheres to the highly desirable principles of benchmark datasets – diversity, richness and scalability. Essentially, 95 categories organized into a hierarchical scene category network were used as search queries sent to Google Earth to obtain the images.

The resulting dataset comprises 1,000,848 non-overlapping remotes sensing scenes in RGB format. RGB is the typical format used as input to the deep learning models in the context of remote sensing image scene classification. The size of images in the dataset varies from  $110 \times 110$  to  $31,672 \times 31,672$  pixels due to the fact that they were captured using different types of sensors. For learning of the pre-trained model on the pretext task, we use the MillionAID images without the labels/queries used to construct it. The learned model can then be applied to different downstream tasks.

#### 2.3 Downstream tasks

The performance evaluation of SSL methods involves assessing their effectiveness on downstream or target tasks. The pre-trained model obtained through the self-supervised setup from the pretext task is transferred to these specific tasks. Transfer learning facilitates the utilization of learned representations from models pre-trained on significantly larger image datasets, enabling downstream models to benefit from this knowledge. As a result, these models often exhibit improved generalization power while requiring fewer training data and iterations. This advantage is particularly valuable for tasks that originate from smaller datasets.

Based on the number of semantic labels assigned to the images in the datasets, image scene classification tasks can be further divided into multi-class (MCC) and multi-label (MLC) classification. In multi-class classification, each image is associated with a single class or label from a predefined set. The objective is to predict one and only one class for each image in the dataset. On the other hand, in multi-label classification, images can be associated with multiple labels from a predefined set based on the available information. The goal is to predict the complete set of labels for each image in the dataset.

We use 9 MCC datasets and 5 MLC datasets to benchmark and evaluate the performance of the self-supervised models in different contexts. The MCC datasets include Eurosat, UC Merced, Aerial Image Dataset (AID), RSSCN7, Siri-Whu, Resisc45, CLRS, RSD46-WHU, and Optimal31. The MLC datasets include AID (mlc), UC Merced (mlc), MLRSNet, Planet UAS, and BigEarthNet (the version with 19 labels). More detailed description of these datasets is given in [4].

# 3 Experimental setup

The research hypothesis posed in Section 1 was tested by comparing the performance of two types of pre-trained models: *i*) model learned by self-supervised iBOT using the unlabeled MillionAID data and *ii*) model learned by supervised Vision transformer (ViT) [6] using the labeled ImageNET-1k dataset (version V1) [9]. Figure 1 illustrates the experimental pipelines. After the training of both models (self-supervised iBOT and supervised ViT), they are transferred via fine-tuning to the specific downstream tasks (labeled remote sensing image scene classification datasets). We next present the transfer learning strategies evaluated in this work as well as the specific implementation details and settings.

### 3.1 Transfer learning strategies

With transfer learning the learned models are applied on the downstream tasks. Two strategies for transfer learning are being used: (1) Linear probing (or linear classification) by updating the model

weights only for the last, classifier layer or (2) Fine-tuning the model weights of all layers in the network. The former approach, retains the values of all but the last layer's weights of the model from the pre-training, keeping them 'frozen' during the training on the downstream task. The latter, on the other hand, allows the weights to change throughout the entire network during fine-tuning on the downstream task. In juxtaposition with these strategies, we evaluate ViT models trained from scratch (i.e., initialized with random weights) on the downstream tasks.

# 3.2 Implementation details and settings

For the downstream tasks, we use the train, validation, and test splits of the image datasets provided within the AiTLAS: Benchmark Arena – an open-source EO benchmark suite available at https://github.com/biasvariancelabs/aitlas-arena. We use the train splits for model training, while the validation splits are employed for parameter selection and search. We apply early stopping on the validation split to prevent overfitting, saving the best checkpoint or model based on the lowest validation loss. The best model is then evaluated on the test split to estimate its predictive performance.

To enhance the model's robustness, we incorporate *data augmentation* techniques during training. The process involves resizing all images to  $256 \times 256$  pixels, followed by random crops of size  $224 \times 224$  pixels. Additionally, random horizontal and/or vertical flips are applied. During the evaluation of predictive performance, when applying the model to test data, the images are first resized to  $256 \times 256$  pixels and then subjected to a central crop of size  $224 \times 224$  pixels. We believe that these augmentation techniques contribute to better generalization of our models for a given dataset.

Regarding the parametrization of the deep architectures, we use the ViT-Base model with an input size of  $224 \times 224$  and a patch resolution of  $16 \times 16$  pixels (ViT-B/16). For our experiments, we use the pre-trained model ViT-B/16 trained in a supervised manner on the ImageNet-1K dataset (version V1) from the timm repository [18]. We pre-train iBOT with ViT-B/16 as the backbone for 400 epochs using the MillionAID dataset to obtain the self-supervised model.

During training, we follow the parameter settings suggested in the literature (cf. [19]). To begin with, we evaluate the performance of the models learned using different values of learning rate: 0.01-0.00001. Next, we use ReduceLROnPlateau as a learning scheduler, reducing the learning rate when the loss has stopped improving. Models often benefit from reducing the learning rate by a factor once learning stagnates for a certain number of epochs (denoted as 'patience'). In our experiments, we track the value of the validation loss, with patience set to 5 and reduction factor set to 0.1 (the new learning rate will thus be lr\*factor). The maximum number of epochs is set to 100. We also apply early stop criteria if no improvements in the validation loss are observed over 10 epochs. We use fixed values for some hyperparameters, such as batch size, which was set to 128. We employ RAdam optimizer without weight decay [11] for optimization. RAdam is a variant of the standard Adam, which employs a mechanism that rectifies the variance from the adaptive learning rate. This, in turn, allows for an automated warm-up tailored to the particular dataset at hand.

Regarding the evaluation measures for predictive performance, for the multi-class classification tasks, we report *top-1 accuracy* measure, referred to as' Accuracy', and for multi-label classification tasks, we report macro averaged mean average precision (mAP).

All models were trained on NVIDIA A100-PCIe GPUs with 40 GB of memory running CUDA version 11.5. We configure and run the experiments using the AiTLAS toolbox [5] (available at https:\aitlas.bvlabs.ai). All configuration files for each experiment and the trained models are available in our repository.

#### 4 Results

Table 1 shows the predictive performance of the evaluated methods across both MCC and MLC datasets. More precisely, it lists three groups of results: *i)* training from scratch with random initialization of the model weights, *ii)* transfer learning using linear probing of the pre-trained models (supervised on the ImageNet dataset, self-supervised on the MillionAID dataset), and *iii)* transfer learning using fine-tuning of the pre-trained models (supervised on the ImageNet dataset, self-supervised on the MillionAID dataset).

Table 1: Performance on MCC datasets in terms of accuracy (top) and MLC datasets in terms of mean average precision (bottom). Results cover training from scratch with random initialization of the weights, pre-training on ImageNet in supervised setup and pre-training using iBOT in self-supervised setup. We report the performance from linear probing (better performance is underlined) and fine-tuning as transfer learning strategies. The values listed in bold typeface indicate best performance overall.

Dataset	Rand. init.	Linear probing		Fine-tuning	
		Supervised	iBOT	Supervised	iBOT
Eurosat	95.037	97.056	97.981	98.722	98.963
UC merced	83.095	93.333	96.190	98.333	98.810
AID	79.350	94.950	97.550	97.750	97.800
RSSCN7	86.071	89.464	92.321	95.893	96.607
SIRI-WHU	86.250	89.792	93.542	95.625	97.708
RESISC45	81.016	92.016	<u>95.651</u>	97.079	97.254
CLRS	65.467	87.200	91.133	93.200	93.367
RSD46-WHU	86.466	89.510	92.051	94.238	94.518
Optimal31	62.634	83.602	<u>91.129</u>	94.624	95.699
AID (mlc)	65.581	74.094	78.096	81.540	82.543
UC merced (mlc)	87.142	89.746	90.320	96.699	97.053
MLRSNet	87.250	90.083	94.225	96.410	96.837
Planet UAS	59.414	62.710	64.059	66.804	67.139
BigEarthNet	75.871	68.357	70.961	77.310	79.361

A close inspection of the results reveals the following findings. First of all, the best performing method across all MCC and MLC datasets is the iBOT model obtained in SSL manner (performances given in boldface typesetting).

Second, using pre-trained models clearly helps to improve the predictive performance in both transfer learning strategies. On average, the improvement in performance of pre-trained models over learning from scratch is the largest using fine-tuned SSL models (~16.15% for MCC datasets and ~9.54% for MLC datasets). The improvement is larger with the fine tuning strategy compared to the linear probing strategy. We report the following notable improvements in predictive performance: For the MCC datasets improvements over 15% are reported for the Optimal31, UC Merced, AID, CLRS, and RESISC45 datasets, and for the MLC datasets improvements over 9% are reported for the AID (mlc), UC Merced (mlc), and MLRSnet datasets. Note that training from scratch gives better results than transfer learning with linear probing only for the BigEarthNet dataset, which is not the case for the fine tuning strategy. This is somewhat expected because of the number of images available (500K images in total) for the model and providing it with sufficient information to train a model from scratch with a very good performance.

Third, the SSL models consistently outperform the supervised models across all datasets and both transfer learning strategies. These improvements are to a smaller extent as compared to the improvements compared to the models learned from scratch. The largest differences are observed when using linear probing as a transfer learning strategy: The average improvement of SSL models over the supervised models across the MCC datasets is  $\sim 3.43\%$  and across the MLC datasets is  $\sim 2.53\%$ . The largest differences (larger than 3%) here are observed for the MCC datasets: Optimal31, SIRI-WHU, CLRS and RESISC45, and for the MLC datasets: AID (mlc) and MLRSnet. The differences in performance between SSL and supervised models is smaller when fine tuning is used as a transfer learning strategy (on average less than 1%).

We have further analysed the results by focusing on the performance across the individual labels. The analysis revealed that the largest differences in performance between the SSL and supervised models are often observed for the labels with limited availability of images. This behavior is especially pronounced in the context of MLC datasets.

To further inspect this behavior, we generated activation maps using GradCAM [14] for the fine-tuned models focusing on selected labels from the MLC datasets. These maps show that the SSL models correctly identify regions relevant to the true label assigned to the image. Moreover, the identified regions from the SSL models are more focused on the specific objects of interest as

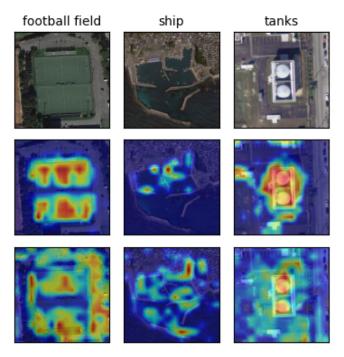


Figure 2: GradCAM visualizations for the predictions made with fine-tuned models on images sampled from the MLC datasets ('football field' from MLRSNet, 'ship' from AID mlc, and 'tanks' from UC Merced mlc): (*first row*) Input images with their ground-truth label, (*second row*) corresponding activation maps from the SSL pre-trained model, (*third row*) corresponding activation maps from the supervised pre-trained model.

compared to the identified regions from the supervised models. This suggests that SSL models possess a stronger capability to discern and highlight the specific objects associated with the labels, leading to improved performance in challenging scenarios.

# 5 Conclusion

We have presented a comprehensive study on the use of self-supervised models in the analysis of remote sensing imagery. The study provides clear protocols for standardization of the experimental work and reproduction of the results and surpasses the preexisting work along several dimensions: number of datasets, diversity in the datasets (number of images, labels, spatial resolution, and label distribution), and machine learning tasks considered (MCC and MLC). We have executed extensive experiments using the iBOT framework for SSL pre-trained using the MillionAID dataset. Its performance was compared against supervised models learned from scratch and using transfer learning.

The presented results from the experiments provide strong evidence that SSL with in-domain training leads to improved predictive performance compared to the supervised models across the 14 datasets used in the study. We summarize the main findings as follows:

- 1. the overall best performing model is the SSL iBOT model obtained with fune-tuning;
- 2. using pre-trained models clearly helps to improve the predictive performance in both transfer learning strategies;
- 3. the SSL models consistently outperform the supervised models across all datasets and both transfer learning strategies; and
- 4. SSL models correctly identify focused regions relevant for the true label assigned to an image.

The immediate line of further work considers studying and understanding the performance of the SSL models in relation to the different dataset properties as well as to the semantic meaning of

the labels. This entails designing a variety of ablation studies, generation of artificial datasets, and exploration of different deep architectures for SSL.

# Acknowledgment

We acknowledge the support of the European Space Agency ESA through the activity AiTLAS - Artificial Intelligence toolbox for Earth Observation (ESA RFP/3-16371/19/I-NB) awarded to Bias Variance Labs, d.o.o..

# References

- [1] Favyen Bastani, Piper Wolters, Ritwik Gupta, Joe Ferdinando, and Aniruddha Kembhavi. Satlas: A large-scale, multi-task dataset for remote sensing image understanding. *arXiv preprint* arXiv:2211.15660, 2022.
- [2] Mathilde Caron, Hugo Touvron, Ishan Misra, Hervé Jégou, Julien Mairal, Piotr Bojanowski, and Armand Joulin. Emerging properties in self-supervised vision transformers. In *Proceedings of the International Conference on Computer Vision (ICCV)*, 2021.
- [3] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. Bert: Pre-training of deep bidirectional transformers for language understanding. *arXiv preprint arXiv:1810.04805*, 2018.
- [4] Ivica Dimitrovski, Ivan Kitanovski, Dragi Kocev, and Nikola Simidjievski. Current trends in deep learning for earth observation: An open-source benchmark arena for image classification. *ISPRS Journal of Photogrammetry and Remote Sensing*, 197:18–35, 2023.
- [5] Ivica Dimitrovski, Ivan Kitanovski, Panče Panov, Ana Kostovska, Nikola Simidjievski, and Dragi Kocev. Aitlas: Artificial intelligence toolbox for earth observation. *Remote Sensing*, 15(9), 2023.
- [6] Alexey Dosovitskiy, Lucas Beyer, Alexander Kolesnikov, Dirk Weissenborn, Xiaohua Zhai, Thomas Unterthiner, Mostafa Dehghani, Matthias Minderer, Georg Heigold, Sylvain Gelly, et al. An image is worth 16x16 words: Transformers for image recognition at scale. *arXiv* preprint arXiv:2010.11929, 2020.
- [7] Kaiming He, Xinlei Chen, Saining Xie, Yanghao Li, Piotr Dollár, and Ross Girshick. Masked autoencoders are scalable vision learners. In 2022 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), pages 15979–15988, 2022.
- [8] Kaiming He, Haoqi Fan, Yuxin Wu, Saining Xie, and Ross Girshick. Momentum contrast for unsupervised visual representation learning. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, June 2020.
- [9] Alex Krizhevsky, Ilya Sutskever, and Geoffrey E Hinton. ImageNet classification with deep convolutional neural networks. *Advances in neural information processing systems*, 25:1097– 1105, 2012.
- [10] Hong Liu, Jeff Z. HaoChen, Adrien Gaidon, and Tengyu Ma. Self-supervised learning is more robust to dataset imbalance. In *International Conference on Learning Representations (ICLR)*, 2022.
- [11] Liyuan Liu, Haoming Jiang, Pengcheng He, Weizhu Chen, Xiaodong Liu, Jianfeng Gao, and Jiawei Han. On the variance of the adaptive learning rate and beyond. In *Proceedings of the Eighth International Conference on Learning Representations (ICLR 2020)*, April 2020.
- [12] Yang Long, Gui-Song Xia, Shengyang Li, Wen Yang, Michael Ying Yang, Xiao Xiang Zhu, Liangpei Zhang, and Deren Li. On creating benchmark dataset for aerial image interpretation: Reviews, guidances, and million-aid. *IEEE Journal of selected topics in applied earth observations and remote sensing*, 14:4205–4230, 2021.

- [13] O. Manas, A. Lacoste, X. Giro i Nieto, D. Vazquez, and P. Rodriguez. Seasonal contrast: Unsupervised pre-training from uncurated remote sensing data. In 2021 IEEE/CVF International Conference on Computer Vision (ICCV), pages 9394–9403, 2021.
- [14] Ramprasaath R. Selvaraju, Michael Cogswell, Abhishek Das, Ramakrishna Vedantam, Devi Parikh, and Dhruv Batra. Grad-CAM: Visual explanations from deep networks via gradientbased localization. In 2017 IEEE International Conference on Computer Vision (ICCV), pages 618–626, 2017.
- [15] Di Wang, Qiming Zhang, Yufei Xu, Jing Zhang, Bo Du, Dacheng Tao, and Liangpei Zhang. Advancing plain vision transformer towards remote sensing foundation model. *IEEE Transactions on Geoscience and Remote Sensing*, pages 1–1, 2022.
- [16] Yi Wang, Conrad Albrecht, Nassim Ait Ali Braham, Lichao Mou, and Xiaoxiang Zhu. Self-supervised learning in remote sensing: A review. *IEEE Geoscience and Remote Sensing Magazine*, 10(4):213–247, 2022.
- [17] Yi Wang, Nassim Ait Ali Braham, Zhitong Xiong, Chenying Liu, Conrad M Albrecht, and Xiao Xiang Zhu. SSL4EO-S12: A large-scale multi-modal, multi-temporal dataset for self-supervised learning in earth observation. *arXiv preprint arXiv:2211.07044*, 2022.
- [18] Ross Wightman. Pytorch image models. https://github.com/rwightman/pytorch-image-models, 2019.
- [19] Jinghao Zhou, Chen Wei, Huiyu Wang, Wei Shen, Cihang Xie, Alan Yuille, and Tao Kong. ibot: Image bert pre-training with online tokenizer. *arXiv preprint arXiv:2111.07832*, 2021.