

# A BENCHMARK FOR GEOGRAPHIC DISTRIBUTION SHIFT IN SMALLHOLDER AGROFORESTRY: DO FOUNDATION MODELS IMPROVE OOD GENERALIZATION?

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## ABSTRACT

Recent improvements in deep learning for remote sensing have shown that it is possible to detect individual trees using high resolution satellite remote sensing data. However, there has not been an evaluation of the robustness of individual tree detection methods to distribution shifts across varying geographies, and this limits the applicability of these methods to diverse areas beyond the sites in which they were trained. To address this, we introduce a benchmark dataset comprising varying agro-ecological zones for remote sensing tree detection in agroforestry farms in India. We then use this dataset to conduct a geographic robustness evaluation of out-of-distribution performance of different deep learning approaches for remote sensing tree detection. Results indicate strong performance of deep learning in detecting trees under conventional evaluation, yet a significant drop in performance in out-of-distribution agro-ecological zones for baseline methods. We report some improvements with foundation model based approaches including SAM and Grounding DINO, but find that they also exhibit similar performance drops out-of-distribution. Our study pushes the boundaries of current research by challenging machine learning methods with a dataset and evaluation protocol that better represents real-world variability, shedding light on the robustness and adaptability of different individual tree detection methods.

## 1 INTRODUCTION

Agroforestry, or integrating trees and crops together into agricultural systems, has been promoted as a high-potential solution for scaleable carbon removal (Chapman et al., 2020) with many co-benefits (Nair & Garrity, 2012) (Hendershot et al., 2023). However, there currently exists limited data on the extent and type of different agroforestry practices (Hart et al., 2023). In the past, remote sensing data has been too low resolution to distinguish between different types of agroforestry practices that involve the integration of trees with other crops in farmland (Schnell et al., 2015). As Bégué et al. (2018) note, “Agroforestry is a challenging cropping system to monitor using remote sensing because of its spatial heterogeneity and complexity...” However, earth scientists have recently reported large accuracy improvements for detection of individual trees using deep learning algorithms and high resolution satellite imagery (Brandt et al., 2020). These advances open up the prospect of monitoring every tree on earth (Hanan & Anchang, 2020) and have enabled entirely new applications like quantifying the total stock of carbon in all of the individual trees continental North Africa (Tucker et al., 2023). However, these large-scale applications require accuracy that is unbiased over large areas, whereas in monitoring, reporting, and verification (MRV) of carbon removal from agroforestry practices, local accuracy in the area of a particular project is more important (Hart et al., 2023). Brandt et al. (2020) noted that “Owing to the high latitudinal variations in vegetation and soil background and to avoid misclassifications in the very sparsely vegetated Sahara desert, we trained two separate models,” but they provide little explanation for how they chose what training data to use for the two separate models, nor do they release the training and evaluation datasets or accuracy of these models in different geographic areas. This means that despite methodological advances, researchers who are applying machine learning to remote sensing data to detect individual trees find it difficult to evaluate the extent to which different tree detection methods or datasets are robust across varying geographies. The machine learning community has identified this problem under names

including distribution shifts (Koh et al., 2021), domain adaptation (Ganin & Lempitsky, 2015), and transfer learning (Xie et al., 2020). It has been recognized as a significant bottleneck to realizing the full potential of real-world remote sensing applications (Koh et al., 2021). Inspired by these issues, we start with quantifying how baseline deep learning approaches for object detection perform at individual tree detection using 50 cm satellite imagery (Labs, 2024) and show that it achieves comparable performance to Brandt et al. (2020). We then compare in-distribution performance on agro-climatic zones in which the model was trained to out-of-distribution performance in other agro-climatic zones, and we find a significant drop in performance out-of-distribution. Finally, we apply recently released computer vision foundation models including Segment Anything and Grounding DINO to our benchmark and find that though they slightly improve accuracy, there persists a large difference between in-distribution and out-of-distribution performance. Our main contributions are (1) a geographic distribution shift benchmark dataset for detecting individual trees across different agro-climatic zones with evaluations for baseline methods and (2) an empirical investigation demonstrating that though computer vision foundation models slightly improve adaptation to geographic distribution shifts under different fine-tuning and few-shot settings, they remain vulnerable to geographic distribution shifts.

## 1.1 RELATED WORK

Recently, Ouaknine et al. (2023) published *OpenForest: A data catalogue for machine learning in forest monitoring* which provides a thorough review of publicly available forest remote sensing benchmark datasets. These datasets are highly concentrated in western countries, and they find only two datasets that enable object detection of individual trees: the NEON Tree Evaluation (Weinstein et al., 2019), an individual tree detection aerial imagery dataset published by the US Government network NEON, and Reforestree (Reiersen et al., 2022), a tree object detection dataset collected from aerial images with 2 cm resolution. Though these have been important contributions, their quality and consistency is low upon closer inspection, and they have limited geographic diversity, which is essential to real-world applications. A significant recent contribution was Beery et al. (2022), the first tree species classification dataset to explicitly integrate geographic distribution shift evaluations. However, this dataset focused on species classification and ignores the task of individual tree detection, which is required for monitoring agroforestry systems. There have been many methods proposed for improving robustness to distribution shift. Some of them such as meta learning (Russwurm et al., 2020) and unsupervised learning (Ganin & Lempitsky, 2015) have demonstrated promising results in addressing specific distribution shifts, while other systematic studies of domain adaptation methods find that most adaptation methods provide little performance improvement out-of-distribution (Taori et al., 2020). Some have reported large improvements in accuracy out-of-distribution from using foundation models (Radford et al., 2021) (Li et al., 2022) (Zhao et al., 2023), but the extent to which foundation models address geographic distribution shift issues in remote sensing remains under-explored.

## 2 DATASET

We frame the individual tree detection problem as an object detection task where the model predicts bounding boxes for each individual tree. To achieve this, we worked with local partners to construct a ground truth annotated dataset of satellite images from agricultural land in Rajasthan, India, where different forms of agroforestry are a common agricultural practice across the state. We source RGB Skysat images (50cm spatial resolution) from the Planet Labs API. To ensure that we could evaluate performance under geographic distribution shift, we conduct a stratified random sample of imagery from the state of Rajasthan according to a map of 8 agro-climatic zone boundaries based on a classification used by the state government, using some filters we detail in supplement Section 1. Then, we break these scenes into 400 x 400 pixel RGB images for annotation. We trained two annotators to use the CVAT platform (Corporation) to annotate individual segmentation masks for each green tree crown in the image. Following Brandt et al. (2020) we require each tree to have an associated shadow to aid visual distinction between trees and other vegetation such as shrubs. To ensure our tree annotations were high quality, we double annotated 400 images and measured inter-annotator agreement of 86 AP, setting a baseline for human performance and ensuring annotation consistency. For ground-truth field data comparison, we also collected field data tree inventories for 38 field plots, and found that 94 percent of trees tagged in the field were correctly detected.

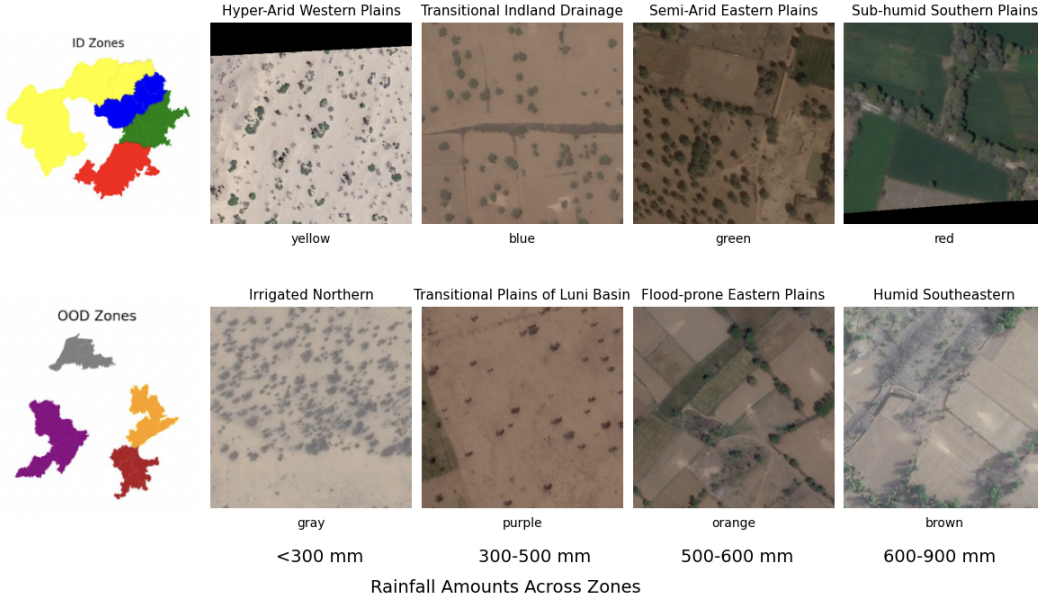


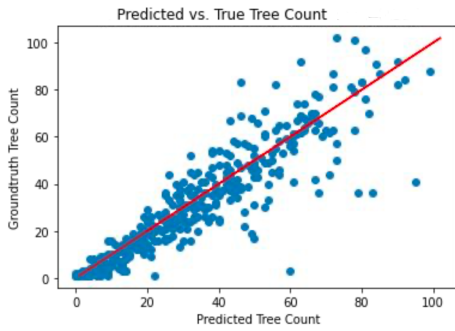
Figure 1: Example Images from different Agro-climatic zones.

### 3 METHODS

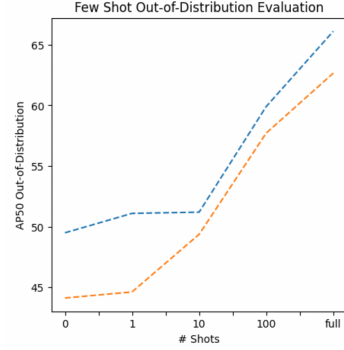
To conduct a distribution shift evaluation, we split our dataset of images for each of Rajasthan’s 8 agro-climatic zones into train and test images. We then split the zones into 4 In-Distribution (ID) zones and 4 Out-of-Distribution zones (OOD), as shown in figure 1. We train under 3 evaluation settings. 1) Conventional Model Evaluation: Train on training splits for all zones, evaluate on test splits for all zones. This is similar to the type of cross-validation that is standard in most machine learning for remote sensing research. 2) Distribution shift Evaluation: Train on train splits for ID Zones, Test on test splits for ID Zones vs. OOD Zones. This evaluation will measure the difference between performance on the ID test set sampled from the same agro-climatic zones the model was trained on to with the OOD test set sampled from agro-climatic regions outside the one in which it was trained. 3) Few-shot adaptation evaluation: Train on train splits for ID Zones, plus  $k$  examples from the training splits of each of the OOD zones. We report Average Precision, a common object detection evaluation metric. We also measure Tree Count R2 to directly compare accuracy metrics to the results from Brandt et al. (2020) The conventional evaluation exactly matches the evaluation protocol of Brandt et al. (2020), so these results will confirm whether or not we reproduced the tree detection accuracy levels from the recent nature article using deep learning to map trees. For our baseline, we train a faster-rcnn model (we report hyper-parameters in the supplements). For our foundation model experiments, we select two foundation models that have been influential in recent computer vision research: the Segment Anything Model (Kirillov et al., 2023) and Grounding DINO (Zhao et al., 2023). Inspired by recent work demonstrating that fine-tuning foundation models can sometimes reduce their performance out-of-distribution, for each model (Kumar et al., 2022), we perform finetuning under three different settings: full fine-tuning, head fine-tuning with a frozen backbone, and head fine-tuning then full fine-tuning. We can directly fine tune Grounding DINO as it is an object detection model, but because the Segment Anything Model requires a prompt embedding, we add a mask-rcnn head on the SAM encoder to perform automatic object detection.

### 4 RESULTS

As shown in Figure 2, We find that the faster-rcnn baseline achieves 0.91 Tree Count R2 on the conventional evaluation ID test set, comparable to Brandt et al. (2020) achieving 0.95 Tree Count R2, which suggests our model is close to theirs. This means that recent advances in tree detection are relatively reproducible with baseline methods as long as a big enough high-quality ground truth dataset is present. When we compare the out-of-distribution results for the model trained on



(a) Figure 2: Predicted vs. true tree counts on the in-distribution test set, the same evaluation protocol as Brandt. Et. al, Nature



(b) Figure 3: Few-shot OOD Evaluation of Grounding DINO (blue) and Faster-RCNN (orange)

all zones with the model just trained on in-distribution zones, we observe more than a 20 percent drop in performance. This suggests that although baseline supervised deep learning methods show strong performance when measured under traditional model evaluation, they are highly vulnerable to reductions in performance under geographic distribution shift. However, the fact that even the conventional evaluation performs 10 percent lower on the out-of-distribution set also suggests that different areas might have different inherent levels of difficulty, and we report a wide range of accuracy in agro-climatic zones in Supplementary Table 1.

Table 1: Comparison of In-Distribution and Out-of-Distribution Average Precision

Method	Eval type	ID AP	OOD AP
Faster-RCNN	Conventional Eval	0.778	0.631
Grounding DINO	Conventional Eval	0.821	0.667
Faster-RCNN	Dist shift eval	0.778	0.441
SAM Finetune Full Finetune	Dist shift eval	0.781	0.485
SAM Finetune Head	Dist shift eval	0.777	0.483
SAM Finetune Head then Full	Dist shift eval	0.592	0.417
Grounding DINO Full Finetune	Dist shift eval	0.814	0.495
Grounding DINO Finetune Head	Dist shift eval	0.810	0.505
Grounding DINO Finetune Head then Full	Dist shift eval	0.808	0.487

As shown in table 1, both SAM and Grounding DINO slightly improve over the faster-rcnn model both in-distribution and out-of-distribution, but they still show a similar pattern of large differences between in-distribution and out-of-distribution performance. When we perform the few-shot evaluation in Figure 3, we find that the grounding DINO model gives larger gains on out-of-distribution data when no data from that domain is available, suggesting that foundation models may be slightly more robust than baseline object detection models. However, baseline performance comes close to matching grounding DINO with 10 in-distribution examples, suggesting that getting small amounts of in-domain data can compensate for adaptation to distribution shifts.

## 5 DISCUSSION

These results suggest that high overall accuracy metrics using traditional cross-validation for deep learning tree detection models can hide poor out-of-distribution generalization performance. Though foundation models did slightly improve performance, these improvements are not large enough not justify their increased scale and cost. Perhaps foundation models that are trained on diverse remote sensing data can provide the generalization that they have demonstrated in other distribution shift evaluations, but further work is needed evaluating approaches to solving distribution shift challenges in remote sensing applications in machine learning. We hope that our benchmark will enable researchers who are interested in machine learning for remote sensing of trees to measure the extent to which the approaches they develop can improve robustness to geographic distribution shift.

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## 1 Supplementary Section 1: The conditions we used to filter images

1. Contained in State of Rajasthan.
2. Published 2021 or later.
3. Captured during the dry season, between March and June.
4. Contains greater than 60 percent cropland or pasture according to ESRI LULC product.
5. Manually filtered out images that are too blurry or low quality to detect trees accurately.

## 2 Supplementary Section 2: Training details

For our hyperparams, we use a faster-rcnn with a resnet-101 backbone and feature pyramid network pre-trained on COCO with a batch size of 16, a learning rate of 0.01 that we divide by 2 every 2000 batches. For Grounding DINO and SAM, we use the default hyperparameters in the mm-detection and huggingface repos respectively.

## 3 Supplementary Table 1

Table 1: Zone Wise AP Metrics for Conventional Evaluation Faster-RCNN

Name of Zone	Value
AP	73.9339
Arid Western Plains	60.866
Transitional Plains of Inland Drainage	88.099
Transitional Plains of Luni Basin	51.197
Semi-Arid Eastern Plains	56.556
Flood Prone Eastern Plains	69.562
Sub-Humid Southern Plain & Aravalli Hills	76.602
Humid South-Eastern Plain	58.547