
GET YOUR EMBEDDING SPACE IN ORDER: DOMAIN-ADAPTIVE REGRESSION FOR FOREST MONITORING

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ABSTRACT

Image-level regression is an important task in Earth observation, where visual domain and label shifts are a core challenge hampering generalization. However, cross-domain regression with remote sensing data remains understudied due to the absence of suited datasets. We introduce a new dataset with aerial and satellite imagery in five countries with three forest-related regression tasks. To match real-world applicative interests, we compare methods through a restrictive setup where no prior on the target domain is available during training, and models are adapted with limited information during testing. Building on the assumption that ordered relationships generalize better, we propose manifold diffusion for regression as a strong baseline for transduction in low-data regimes. Our comparison highlights the comparative advantages of inductive and transductive methods in cross-domain regression.

Keywords Dataset · Regression · Remote sensing · Domain adaptation

1 Introduction

Distribution shifts between the training data and testing data are ubiquitous in computer vision. While it is generally accepted that a model trained on sufficient data has some ability to generalize to new target data, in practice visual variations induce significant performance drops [3].

A good example can be found in vegetation mapping and monitoring tasks. Biodiversity monitoring, carbon tracking, resource management, and food security analysis heavily depend on a regular assessment of forest resources through important parameters such as tree counts or height. A practical solution is to train image models to regress such values

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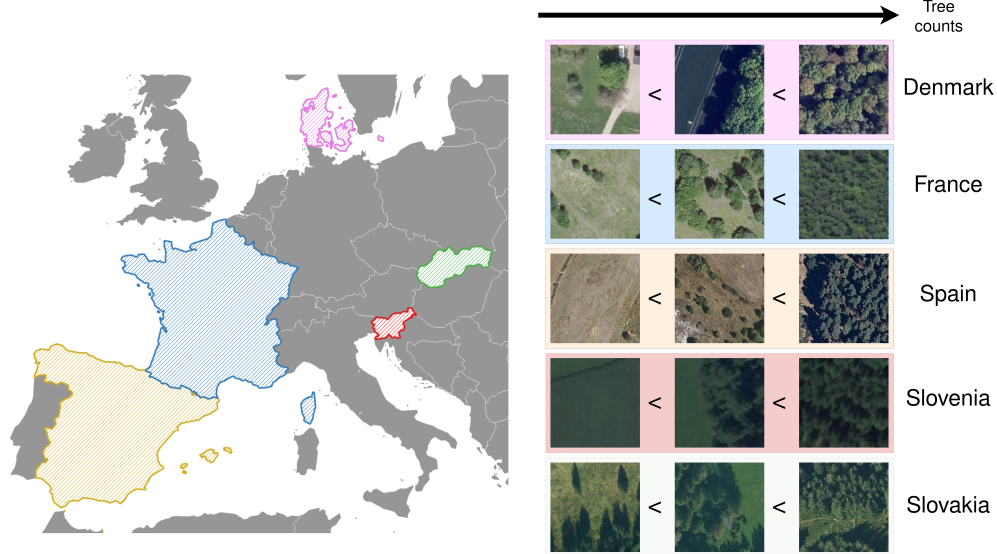


Figure 1: **Vegetation regression across countries.** We hypothesize that order relations generalize better through visual and label domains than direct regression. Predicting tree counts directly requires domain-specific knowledge about local species, whereas predicting ordered chains remains intuitively easy.

from satellite or aerial imagery [7, 28]. However, models trained on remote sensing imagery are usually limited to one area and perform poorly on others, due to different spectral ranges, ground resolutions, or visual patterns [49, 34, 47].

Data availability and downstream applications define the scope of models (regional [29] - national [36] - continental [5]), but they don’t necessarily match the visual and semantic domains defined by biomes and environmental conditions. Intuitively, a model trained on a dataset should perform relatively well on datasets that are spatially close and visually similar, although it remains unclear to what extent.

To better assess generalization performance and go towards universal models that can be trained in countries with high data availability and applied to any country without prior knowledge or retraining, we introduce the DRIFT² dataset for universal, low-data domain-adaptive regression.

Building on recent advances in order learning, we hypothesize that order relationships generalize well across domains. We enforce a well-ordered embedding space in the source domain, then adapt to target domains in low-data setups. Notably, we show that this strong regularization during training does not hamper source-domain performance **and** creates a clean embedding space to propagate similarities at test-time, which opens the way for advanced low-data inference in the form of manifold diffusion. Our contributions are as follows:

- We publish a large-scale dataset across five countries in Europe for domain-adaptive regression, using both aerial and satellite imagery, with a panel of tasks related to forest monitoring.
- We compare inductive and transductive methods across datasets and tasks, in a low-shot universal and source-free domain adaptation setup. We show that transductive methods take advantage when the domain gap becomes predominant.
- We introduce a simple but effective baseline for domain-adaptive regression. We propose a generalization of graph diffusion, a common technique for semi-supervised classification, to image-level regression. Our experiments demonstrate the applicative potential and superiority over common baselines.

2 Related work

2.1 Order learning

The seminal work of [32] introduced order learning as an alternative to direct regression, with the motivation that in certain cases, it is easier to compare images (this person is older than this other person) than to associate them

²Dataset will be made publicly available upon publishing

independently with a scalar. Subsequent works built on this idea with iterative predictions [42], partial ordering [23] and further constraints on the geometry of the embedding space [24]. Our work builds on the latter. In a cross-domain setup, we hypothesize that the highly constrained embedding space with geometric constraints in the source domain generalizes better to other domains.

2.2 Cross-domain regression

Existing works have tackled domain adaptation through three main setups, depending on the available information about the target domain.

Unsupervised domain adaptation trains on unlabeled images of the target domain. Some works have focused on aligning features of the source and target domain with dedicated mechanisms to limit scale [8] or embedding structure [37] shifts, so that the regressor maintains its performance on the target domain. Adversarial training [35] has been proven effective as a tool to learn a domain shift metric.

Semi-supervised domain adaptation, in contrast, assumes that some labeled images are available in the target domain. A common approach is to weight training points to minimize the performance gap [48], or as a form of boosting [39]. Few-shot domain adaptation can be considered a special case of semi-supervised adaptation, where the number of target domain labeled samples is very limited. A good example is the work of Teshima et al. [46], where authors generate synthetic target domain samples with the assumption that generative modeling offers more invariance.

These setups have limited applicability in many real-world problems due to the fact that utilizing labeled or unlabeled data from the target domain during training requires specific training for each target domain.

Source-free domain adaptation removes the liberty of modifying the source domain training phase, which is not always possible in real settings. Models are only adapted at test-time, when applied on the target domain. In the context of image classification, the popular SHOT [31] method introduced information maximization and self-supervised learning as promising ideas for label-free target domain fine-tuning. If a few labeled samples are available, simple fine-tuning on the target domain with suited regularization remains a strong baseline [25]. We are not aware of works exploring this for regression.

Here, we aim at building a model that can be quickly adapted to any target domain, without any prior knowledge of that domain. As such, we prepare the model for generalization on the source domain, only with source domain data. At test-time, we explore low-data configurations, with very limited information available on the target domain for quick adaptation. This setup has been labeled as **universal source-free domain adaptation** [21] in the context of classification.

2.3 Image-level regression in Earth observation

The increasing availability of vast and diverse collections of remote sensing imagery and datasets presents both opportunities and challenges for computer vision tasks. To date, most works utilizing remote sensing imagery focus on image classification and semantic segmentation [2, 40, 4]. For example, to count trees, some works rely on the detection of individual trees [26, 5], but manual annotation relies on expert knowledge and is extremely time-consuming. Given the variations in ground resolution, image quality, and geographic areas, small objects and occlusion phenomena can make exhaustive annotation virtually impossible. Other labels on woody biomass or canopy height cannot be manually labeled. Therefore, labels often have to be sourced from field measures [30, 9], or derived from low-resolution dedicated sensors such as GEDI [22, 13], and remain noisy due to the varying viewing angles, technical inaccuracies in positioning systems [15] or temporal mismatch [45, 6]. As such, accurate labels are often found at a lower resolution than the ground resolution of the image. This makes image-level regression a core task in computer vision for Earth observation, as it offers a way to directly predict the information at the available resolution [12, 7]. To our knowledge, there is no existing dataset for cross-domain image-level regression using sub-meter resolution remote sensing imagery.

3 DRIFT: Domain-adaptive Regression for Forest Monitoring across Countries

We introduce the DRIFT dataset (Domain-adaptive Regression for Image-level Forest moniToring), including 25k images in five European countries from aerial and nanosatellite imagery, with three target variables to predict for each image:

1. Canopy height: average height value for pixels containing woody vegetation.
2. Tree count: number of overstory trees in the images.
3. Tree cover fraction: percentage of the image being covered by overstory tree crowns.

Dataset collection. We built the dataset from national aerial orthophotography with various ground sampling distances (GSD) for Denmark, Spain, France, and Slovakia. All aerial images contain three spectral channels: Red (R), Green (G), and Blue (B). For Slovenia, we used very high-resolution satellite imagery from commercial nanosatellites (SkySat). We acquired the orthorectified surface reflectance products at a spatial resolution of 50cm.

Table 1: Dataset characteristics. GSD and Height in meters, Cover in percents.

Country	# Images	Patch size	Sensor	GSD	Timeframe	Height	Range Count	Cover
Denmark	13094	200	aerial	0.2	2018	[0, 38]	[0, 192]	[0, 100]
France	10298	250	aerial	0.2	2018-20	[0, 28]	[0, 204]	[0, 100]
Slovakia	3129	250	aerial	0.2	2021	[1, 38]	[0, 148]	[0, 100]
Spain	1150	200	aerial	0.25	2020	[0, 29]	[0, 135]	[0, 100]
Slovenia	1903	100	satellite	0.5	2021	[0, 36]	[0, 91]	[0, 100]

Dataset annotation. Aerial LiDAR is an accurate source of 3D structure information to characterize trees across various landscapes [50, 20, 19]. With the high-resolution height information, trees can be separated from other objects and measured in height and crown width. We first rasterized the LiDAR data to Canopy Height Models (CHMs), where each pixel indicates the top height of vegetation at this location, if there is any. Image-level canopy height was calculated by averaging all non-zero height values in the image, and tree cover fraction was extracted with 5-meter height thresholding to aggregate areas covered by vegetation taller than 5m [1]. Regarding tree counts, we used a public imagery-based tree counting model for Denmark, which was trained using point supervision with 22k tree annotations [27]. For the rest, we processed CHMs to extract tree crown centers with local peak identification over a sliding window with adaptive size [41]. CHMs were preprocessed with a conditional filter for higher separability of low foliage or artifacts [9]. We adjusted image-level counts with linear correction. All hyperparameters were fit on a small labeled set ($\approx 1k$ trees) for each country, and we report the 3-fold R^2 score on random train/validation splits for correction in Supplementary Table 1.

Challenges. The DRIFT dataset includes significant shifts between label and visual distributions (see Fig. 2) due to sensor and area differences (see distribution of biomes in Supplementary Fig. 2). Moreover, within a tree species, individuals can exhibit different behaviors depending on their direct environment and living climate, which introduces concept drift: visually similar trees can vary in height [18]. Such variations can also be influenced by sensor properties such as the viewing angle.

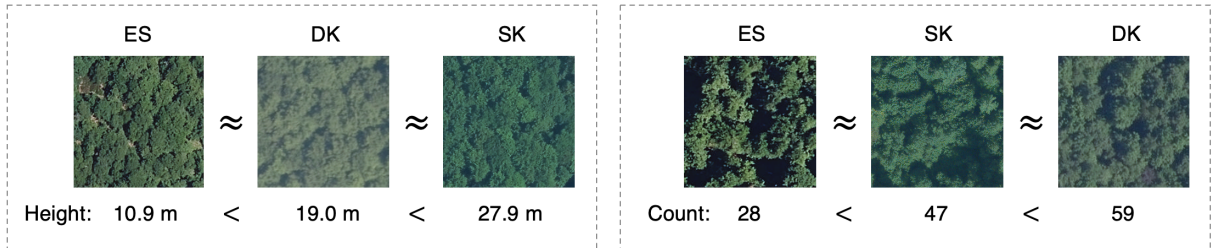


Figure 2: Challenging examples in the DRIFT dataset: despite similar visual content, images can have different values in the label space. More visual examples can be found in Supplementary Fig. 1

Label shift. The DRIFT dataset exhibits a substantial shift in label distribution across countries. We plot the label shift in Fig. 3 between all possible pairs of annotation subsets in DRIFT.

Regression tasks. Canopy height, tree count, and tree cover heavily depend on tree species, local climate, and landscape characteristics. Height prediction from optical images is inherently challenging due to limited visual clues about depth from an aerial viewpoint, especially if the ground is not visible, but it has been proven possible using satellite imagery [22, 33]. Counts depend on the model’s interpretation of individual crown area, which is subject to extreme variations even within a species [18]. Cover fraction is intuitively the easiest, as the model only needs to separate trees from background pixels. The difficulty depends on the level of similarity between short vegetation ($< 5m$) and tree cover.

Proposed splits. We propose to use two countries (Denmark and France) with abundant high-quality CHM data as source domains for training. For testing, we apply models on three countries (Slovakia, Slovenia, Spain) representing different target domains. The Slovenia subset allows a comparison with another type of sensor (nanosatellites), and

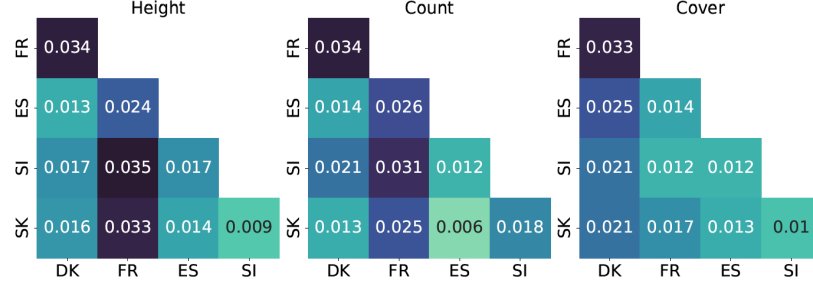


Figure 3: **Label shift across countries.** Wasserstein distances between label distributions in country subsets indicate the level of label shift. Note that the shifts depend on the target variable.

the Spain subset introduces a much drier ecosystem compared to the others. The France and Denmark subsets have different label distributions (Fig. 3), which introduces variation in the comparison of models trained on them.

Evaluation. We propose an evaluation framework for DRIFT that follows common constraints and represents real-world application contexts. First, we consider that no knowledge about the target domain is available during training. A model that can generalize to multiple areas is more valuable than models that are specific to a source/target dataset combination. As such, there is a high interest in going towards "universal" models that do not build on assumptions about their target domain. In a real-world scenario, a model that reached high performance on its source domain will be archived and considered for generalization, preferably with no or little supporting information about the target domain, and no retraining. Second, we consider that some knowledge about the target domain can be accessed at test-time. Following the terminology introduced in [21], we propose to follow a setup of universal source-free domain adaptation for regression, in two stages. In the Procurement stage, or source domain training, models are trained and prepared for generalization. During the Deployment stage, or target domain testing, models are adapted using a few labeled examples. In the following, we refer to this setup as N -shot adaptation.

4 Method

We propose to explore the potential of ordered embeddings and simple transductive learning on the cross-domain challenges of the DRIFT dataset (see Fig. 4). We train the embedding extractor on the source domain, using geometric order learning to enforce structure. We extract embeddings on the target domain, and perform adaptation for regression using a few labeled images. Optionally, we refine predictions to take into account local and global manifold structure with diffusion.

4.1 Preliminaries

We first introduce notations for the problem of few-shot domain adaptation for regression.

Let $\mathcal{D}_s = \{(\mathbf{x}_i^s, y_i^s)\}$ and $\mathcal{D}_t = \{(\mathbf{x}_i^t, y_i^t)\}$ denote the source and target domains respectively. y^s and y^t take continuous values in \mathbb{R} , and we note that their distributions are different. Notably, it is common in vegetation mapping that their support $[y_{min}^s, y_{max}^s]$ and $[y_{min}^t, y_{max}^t]$ differs. For example, $y_{max}^s \neq y_{max}^t$ in height mapping due to different species.

At test-time, we assume that some information about the target domain is accessible, in the form of a few labeled samples, which we refer to as the target domain support set $\mathcal{D}_{ts} \subset \mathcal{D}_t$. Similarly to the common practice in classification [44, 14], we divide the target label set into k_r equally spaced value groups, and construct the target domain support set \mathcal{D}_{ts} by randomly drawing N samples from each group, forming a k_r -way N -shot adaptation setup.

A simple baseline method would be to train a regressor $f(\mathbf{x}) = y$ on \mathcal{D}_s and apply it to \mathcal{D}_t . Due to domain shifts, this performs generally poorly. Instead, we consider a feature extractor $h(\mathbf{x}) = \mathbf{v}$, with $\mathbf{v} \in \mathbb{R}^d$ and $\|\mathbf{v}\|_2 = 1$, and frame the problem as cross-domain transduction: y^t is inferred from the relationships between the embeddings in \mathcal{D}_t .

Geometric order learning (GOL) [24] enforces the notion of order in the embedding space, such that the direction and distance between embeddings reflect the relations between their labels. The framework is based on M reference points that are shared between embeddings of similar values. Consider \mathbf{v}_a and \mathbf{v}_b and the corresponding reference points $r_{\theta(a)}, r_{\theta(b)}$, with θ the function assigning a sample to its reference point. GOL trains with the following composite loss function:

$$L = L_o + L_m + L_c \quad (1)$$

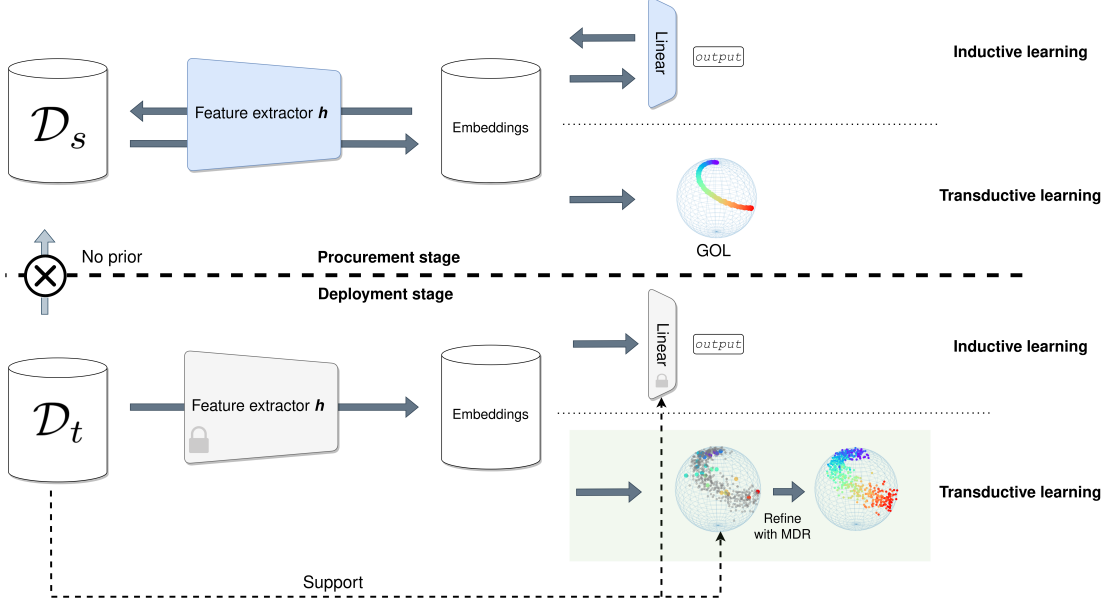


Figure 4: Overview of our universal, source-free domain adaptation framework. The feature extractor (and linear layer for inductive regression) is trained on the source domain \mathcal{D}_s during the Procurement stage, then applied on the target domain \mathcal{D}_t during the Deployment stage. We do not use any prior regarding the target domain when training on the source domain, and do not assume sufficient data is available for training on the target domain. On the target domain, a few labeled examples are available to calibrate or fine-tune inductive methods, and support our proposed manifold diffusion for regression (MDR), a transductive approach.

where

- L_o , the order loss, aligns the embeddings with the direction of their label relation. For the $r_{\theta(a)} < r_{\theta(b)}$ case, $L_o = -\log e^{\vec{u}_+ \cdot \vec{u}_{ab}} / (e^{\vec{u}_+ \cdot \vec{u}_{ab}} + e^{\vec{u}_- \cdot \vec{u}_{ab}})$ with $\vec{u}_+ = (r_{\theta(b)} - r_{\theta(a)}) / \|r_{\theta(b)} - r_{\theta(a)}\|$ the forward direction vector between the reference points of a and b , $\vec{u}_- = (r_{\theta(a)-1} - r_{\theta(a)}) / \|r_{\theta(a)-1} - r_{\theta(a)}\|$ the backward direction vector, and $\vec{u}_{ab} = (\mathbf{v}_b - \mathbf{v}_a) / \|\mathbf{v}_b - \mathbf{v}_a\|$. When $r_{\theta(a)} > r_{\theta(b)}$, the corresponding formula is obtained symmetrically.
- L_m , the metric loss, makes embedding space distances reflect label differences. When $r_a = r_b$, $L_m = \sum_{i=0}^{M-1} \max(|d(r_i, \mathbf{v}_a) - d(r_i, \mathbf{v}_b)| - \gamma, 0)$, with d the Euclidean distance. When $r_{\theta(a)} < r_{\theta(b)}$, $L_m = \sum_{i=0}^a \max(|d(r_i, \mathbf{v}_a) - d(r_i, \mathbf{v}_b)| + \gamma, 0) + \sum_{j=b}^{M-1} \max(|d(r_j, \mathbf{v}_b) - d(r_j, \mathbf{v}_a)| + \gamma, 0)$. That is, all reference points inferior to $r_{\theta(a)}$ pull \mathbf{v}_a closer, while all reference points superior to $r_{\theta(b)}$ push \mathbf{v}_a away, and the opposite for \mathbf{v}_b . The formula for $r_{\theta(a)} > r_{\theta(b)}$ is obtained symmetrically.
- L_c , the center loss, places reference points at the center of embeddings with similar values. $L_c = d(r_{\theta(a)}, \mathbf{v}_a) + d(r_{\theta(b)}, \mathbf{v}_b)$.

We invite interested readers to refer to the original paper for more details.

Lee et al. [24] report that GOL creates a well-ordered embedding space, which allows prediction with a simple distance-based k-nearest neighbors (kNN) assignment to estimate continuous values.

4.2 Manifold Diffusion for Regression

We introduce Manifold Diffusion for Regression (MDR) as an optional post-processing step to refine the predictions. Manifold diffusion [17, 10, 51] is a popular transductive method in semi-supervised learning and image retrieval to exploit the structure of the embedding space for better class predictions. Here, we modify it for regression in the context of cross-domain adaptation.

We start by introducing the diffusion framework originally proposed in [51]. Assuming a set $X = \{\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_n\}$ and $\mathbf{v}_i = h(\mathbf{x}_i)$, the affinity matrix $W \in \mathbb{R}^{n \times n}$ is constructed by calculating the pairwise cosine similarity between samples:

$$a_{ij} := \begin{cases} [\mathbf{v}_i^\top \mathbf{v}_j]_+^\gamma, & \text{if } i \neq j \wedge \mathbf{v}_i \in \text{NN}_k(\mathbf{v}_j) \\ 0, & \text{otherwise} \end{cases} \quad (2)$$

with NN_k the set of k nearest neighbors in X , and γ a hyperparameter. W is non-negative, sparse, and has zero diagonal.

The symmetric normalized form is computed:

$$W_n := D^{-1/2} W D^{1/2} \quad (3)$$

where D is the diagonal matrix $D := \text{diag}(W \mathbf{1}_n)$ with the row-wise sums of W . The normalized graph Laplacian of W is defined as $L := I_n - W_n$. Assuming that we have label information for some of the points, we can iteratively update the graph with $F(t+1) = \alpha W F(t) + (1-\alpha)Y$, where $Y \in \{0, 1\}^{n \times c}$ is the one-hot encoded label matrix for c classes. Zhou et al. [51] noted that this is equivalent to solving the linear system: $F^* := (I_n - \alpha W_n)^{-1} Y$. The final class prediction for a sample i is obtained as $\text{ARGMAX}(F_i)$.

We replace the label matrix Y with the support matrix $S \in \{0, 1\}^{n \times k}$, the one-hot encoded matrix for each of the k labeled samples. $S_{i,j} = 1$ for the first k rows and columns, and zero elsewhere. After solving for $S^* = (I_n - \alpha W_n)^{-1} S$, we obtain an updated similarity score between an image and each of the support elements. S^* captures the structure of the embedding space and creates a refined similarity measure taking into account local and global context.

We output the final regression estimate as the weighted sum of the k_v highest values in S^* and the known labels. Note that this step heavily relies on a well-ordered embedding space: predictions will be unstable if the embedding space does not maintain the order of the one-dimensional continuous label space.

5 Experiments

5.1 Implementation details

During the Procurement stage, we train a ViT-B/16 [11] feature extractor with GOL with $M = k_r = 5$ and equal interval between label groups. For canopy height, the upper bound is set to 25m, and each group spans over 5m. For count, we use 0 as the lower bound and 90 (Denmark) or 70 (France) as the upper bound and split accordingly. For cover, we use 20% as the lower bound and 100% as the upper bound. We weight the order loss L_o , metric loss L_m , and center loss L_c with a factor of 1, 66, and 33, respectively, for similar convergence rates.

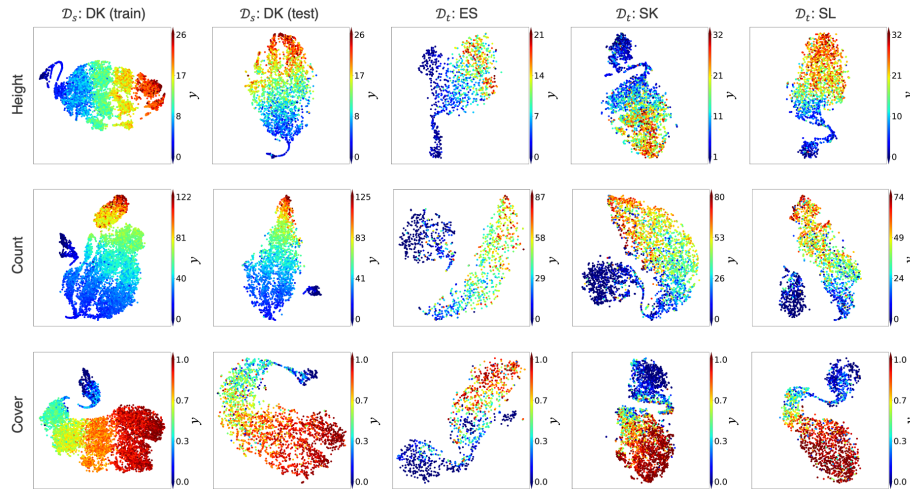


Figure 5: Embeddings retain ordered relations across domains (t-SNE visualization).

During the Deployment stage, we pick the 1% and 99% percentile values of each target variable as the lower and upper bound and split the entire dataset into 5 groups. We implement MDR in a few-shot setup. We use standard hyperparameters that are reported to work well across different setups ($\gamma = 3$, $\alpha = 0.99$) [16], and use the entire support set for diffusion, setting $k = N$ and assigning the final values with $k_v = 2N$, with the effects of k_v shown in Supplementary Fig. 6. We refer to this approach as GOL+MDR.

5.2 Qualitative analysis

We plot projections of the embedding space in the source and target domains across tasks on the DRIFT dataset in Fig. 5. Label order in the embedding space is roughly maintained across domains, but does not necessarily remain in a single well-connected cluster with a clear direction of label space increase. Consequently, kNN label assignment can pick up noisy neighbors from adjacent clusters and wrongly predict.

We plot the effect of MDR on DRIFT examples in Fig. 6. MDR activates more relevant support samples than kNN, i.e., the examples picked up for assigning the prediction are closer to the true value. This comes from taking into account both global and local manifold structure, rather than only the immediate neighbors. Assuming that embeddings remain overall ordered on the target domain, MDR captures higher-order similarities and discards potentially confusing support samples in the target domain. Example predictions can be found in Supplementary Fig. 3 and 4.

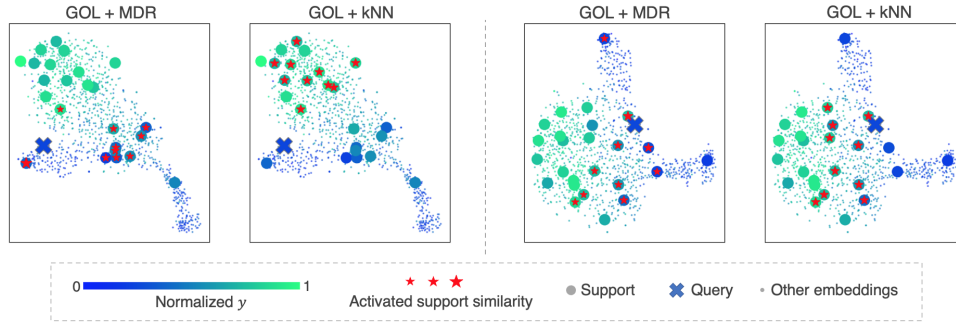


Figure 6: Top 10 support samples activated by GOL+MDR and GOL+kNN in 5-shot setup (t-SNE visualization). Closer colors indicate higher adjacency in the label space.

5.3 Quantitative analysis

5.3.1 Few-shot evaluation.

We present a comparison of our approach with common baselines and state-of-the-art methods in Table 2. We compare against regression on the target domain without adaptation (Regression), regression on the target domain with linear calibration using the support set (Regression cal.), weighted k-nearest neighbor prediction from support examples (kNN), fine-tuning with the support set (FT) [25], geometric order learning with weighted kNN prediction (GOL) [24].

The off-the-shelf regressor has overall low and unstable performance, as expected. Calibration with the support set brings a significant but inconsistent boost in performance. This is particularly visible on the Denmark \rightarrow Spain setup, for which calibration helps only on the cover task. Similarly, fine-tuning sometimes improves performance, but it relies on how well the underlying model generalizes to the target dataset. All inductive methods experience failure cases, with R^2 scores below 0.3 in at least one setup.

Transductive approaches, on the other hand, decouple to some extent the performance on the target domain from the source domain. kNN performs overall more consistently than inductive approaches. It however performs worse than calibrated regression on average. GOL has a similar behavior, with a minor increase in performance undoubtedly due to better regularization in the source domain. GOL+MDR performs the best among transductive approaches, and especially well on the difficult setups of Denmark \rightarrow Spain. Combining with fine-tuning on the support set further increases performance on some setups.

We note that the performance of direct cross-domain regression can serve as an indicator of a multifactorial domain gap. For example, on cover regression, where the label shift is limited, direct regression performs well, except for Denmark \rightarrow Spain which is arguably the largest visual and semantic domain shift (Supplementary Fig. 2). We plot in Figure 7 a pairwise comparison of the two best-performing inductive and transductive methods against off-the-shelf regression

Table 2: Comparison of methods on the DRIFT dataset (5-shot). Average R^2 score across 3 random runs for FT and 10 random runs for the rest.

	Source Target	Spain	Denmark Slovakia	Slovenia	Spain	France Slovakia	Slovenia	avg
Height	Regression	0.35	-.05	0.23	0.61	0.11	0.13	0.23
	Regression cal.	0.17±0.12	0.49±0.10	0.67±0.03	0.61±0.06	0.42±0.06	0.67±0.02	0.50
	FT [25]	0.34±0.00	0.45±0.02	0.60±0.02	0.69±0.01	0.49±0.00	0.50±0.09	0.51
	kNN	0.21±0.06	0.45±0.04	0.68±0.03	0.55±0.04	0.38±0.06	0.63±0.03	0.48
	GOL [24]	0.21±0.12	0.35±0.13	0.67±0.04	0.62±0.05	0.41±0.08	0.65±0.03	0.49
	GOL+MDR	0.60±0.04	0.49±0.06	0.65±0.05	0.65±0.04	0.46±0.05	0.66±0.04	0.59
	GOL+FT+MDR	0.56±0.07	0.57±0.03	0.69±0.01	0.70±0.01	0.47±0.01	0.71±0.01	0.62
Count	Regression	0.53	0.36	0.43	0.51	0.43	0.37	0.44
	Regression cal.	0.51±0.04	0.53±0.05	0.59±0.03	0.53±0.07	0.61±0.04	0.58±0.04	0.56
	FT [25]	0.53±0.00	0.48±0.00	0.60±0.01	0.54±0.00	0.53±0.01	0.40±0.00	0.51
	kNN	0.42±0.07	0.43±0.06	0.55±0.03	0.51±0.06	0.55±0.14	0.55±0.08	0.50
	GOL [24]	0.51±0.03	0.56±0.03	0.58±0.05	0.51±0.05	0.58±0.05	0.46±0.06	0.53
	GOL+MDR	0.51±0.04	0.55±0.06	0.59±0.03	0.54±0.04	0.61±0.03	0.54±0.04	0.56
	GOL+FT+MDR	0.53±0.01	0.49±0.10	0.59±0.05	0.51±0.09	0.63±0.01	0.53±0.03	0.55
Cover	Regression	0.11	0.70	0.81	0.80	0.77	0.76	0.66
	Regression cal.	0.41±0.04	0.75±0.01	0.77±0.04	0.83±0.02	0.79±0.01	0.77±0.04	0.72
	FT [25]	0.27±0.00	0.44±0.22	0.75±0.01	0.81±0.01	0.81±0.00	0.81±0.00	0.65
	kNN	0.47±0.04	0.69±0.02	0.71±0.06	0.75±0.04	0.73±0.05	0.68±0.07	0.67
	GOL [24]	0.51±0.06	0.76±0.02	0.69±0.10	0.81±0.03	0.82±0.02	0.71±0.09	0.72
	GOL+MDR	0.57±0.08	0.71±0.03	0.70±0.06	0.82±0.03	0.79±0.03	0.70±0.06	0.71
	GOL+FT+MDR	0.65±0.05	0.74±0.04	0.64±0.05	0.84±0.01	0.76±0.03	0.70±0.07	0.72

performance drop. When the implied domain gap becomes large enough for inductive methods to fail, transductive methods are favored.

We repeat experiments with VGG16 [43], another popular feature extractor. GOL+MDR and GOL outperformed regression baselines for height and count with a larger margin than using the ViT-B/16 backbone (Supplementary Table 2).

5.3.2 In-domain performance.

We report in Table 3 the performance of GOL in the source domain. As reported in the original publication [24], GOL performs on par with ordinary regression.

Table 3: Source domain test performance. Average R^2 score across two source domains.

Backbone	Model	Height	Count	Cover
ViT-B/16	GOL [24]	0.86±0.05	0.92±0.01	0.87±0.08
	Regression	0.88±0.05	0.90±0.01	0.86±0.09
VGG16	GOL [24]	0.80±0.07	0.91±0.01	0.80±0.13
	Regression	0.84±0.06	0.93±0.01	0.86±0.09

5.4 Ablation studies

We report in Table 4 the effect of removing components of GOL+MDR, averaging across countries in the DRIFT dataset. MDR does not improve performance compared to the baseline when applied without ordered embeddings: the manifold in the target domain is too unstructured to give meaningful similarities. Ordered embeddings (GOL) generalize better in all tasks, and combining GOL+MDR gives the best results in 5 out of 6 experiments.

We further test the sensitivity of different methods to the number of shots (Supplementary Fig. 5), i.e., the number of support samples per group. As often observed in few-shot setups, performance saturates after a certain number of shots

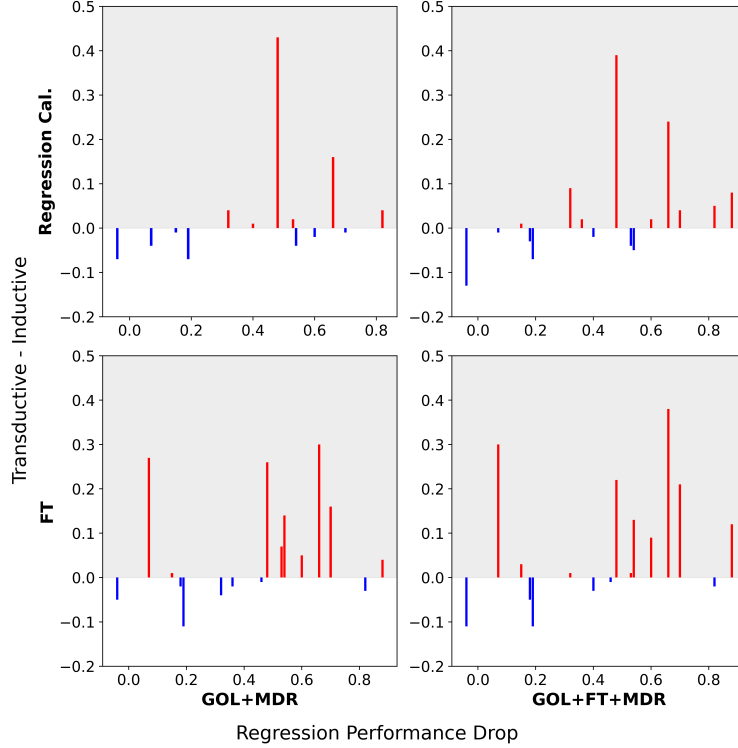


Figure 7: Transductive vs. inductive performance across different setups and tasks. Pairwise performance differences between inductive and transductive methods evolve with off-the-shelf regression performance drop (source domain performance - target domain performance), an ad-hoc indicator of domain gap.

Table 4: Ablation study for GOL+MDR. Average R^2 score across two source domains and three target domains. We report the performance of a model with only the center loss and weighted kNN prediction as the baseline.

Backbone	GOL	MDR	Height	Count	Cover
ViT-B/16	✓	✓	0.59 \pm 0.08	0.56 \pm 0.03	0.71 \pm 0.08
	✓		0.49 \pm 0.17	0.53 \pm 0.04	0.72 \pm 0.10
		✓	0.40 \pm 0.17	0.43 \pm 0.11	0.65 \pm 0.10
			0.48 \pm 0.16	0.50 \pm 0.06	0.67 \pm 0.09
VGG16	✓	✓	0.55 \pm 0.09	0.53 \pm 0.05	0.67 \pm 0.07
	✓		0.47 \pm 0.16	0.51 \pm 0.05	0.64 \pm 0.09
		✓	0.25 \pm 0.16	0.39 \pm 0.11	0.59 \pm 0.08
			0.31 \pm 0.13	0.34 \pm 0.11	0.61 \pm 0.08

[38, 44], here 20. Our proposed GOL+MDR outperforms the other methods on most of the setups, except for the easiest task of tree cover, where finetuning is needed to reach comparable performance as other baselines.

6 Conclusion

We introduce the DRIFT dataset with forest-related image regression tasks across five European countries. We reveal different behaviors depending on tasks and target countries, which underlines the importance of taking into account the domain gap when choosing between inductive and transductive approaches. DRIFT covers a panel of situations with varying levels of difficulty and domain gaps. As such, it is close to real-world conditions, where those factors are difficult to estimate beforehand. In this context, we argue that transductive methods are a good starting point, as they allow qualitative analysis of the embedding space, even before having to label samples for quantitative evaluation. In contrast, inductive approaches remain "black boxes" with poor explainability.

We verify qualitatively and quantitatively that the embedding order can be maintained across domains, which unlocks advanced adaptation with diffusion approaches. This works particularly well in low-data regimes, and when the domain gap is high.

We hope that the DRIFT dataset will encourage researchers to propose new methods for domain adaptation in image-level regression. In future work, we plan on extending the comparison to semi-supervised approaches on the target domain, with a larger dataset covering more domains across other continents.

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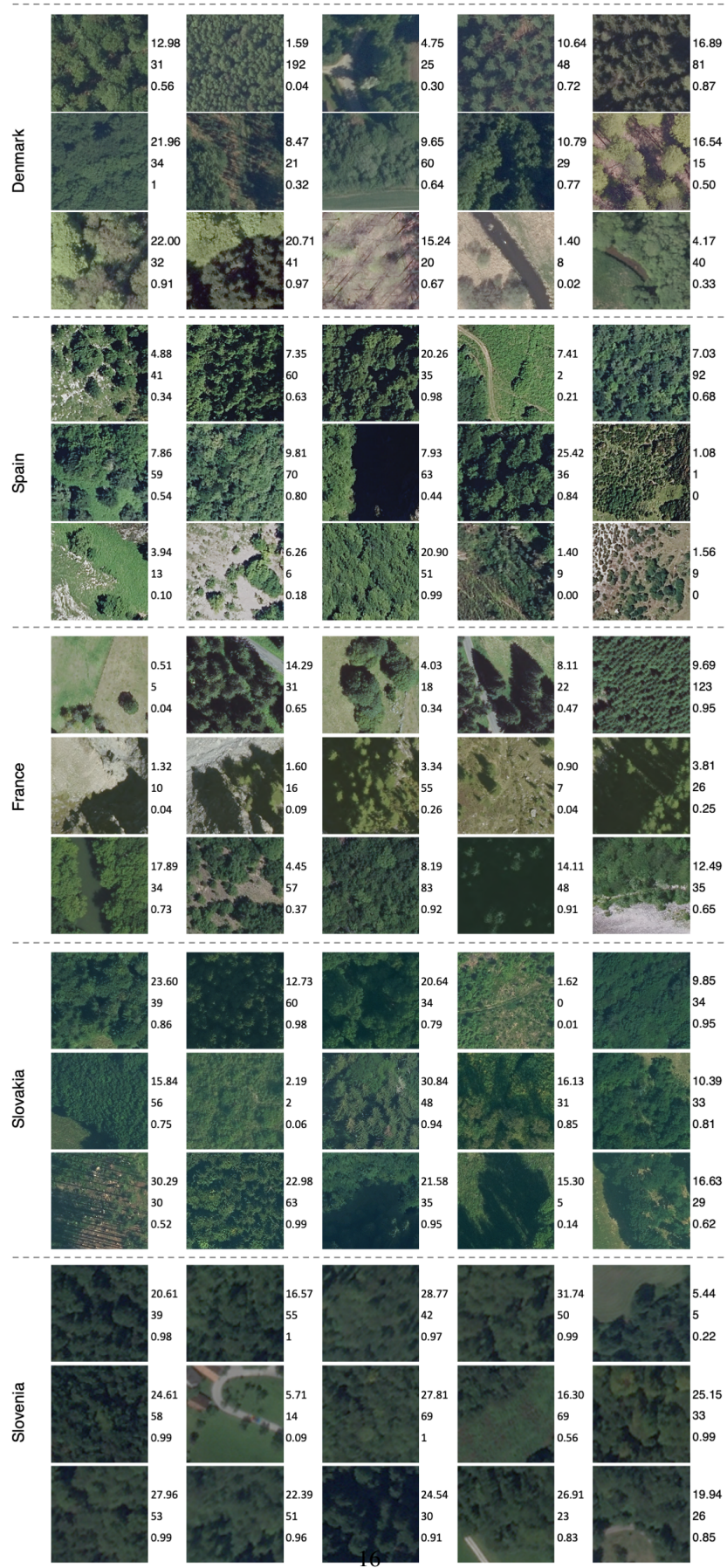
7 DRIFT dataset details

Tree counts. For Denmark, the subset was built from the predictions of [26]. Due to the relatively high reported counting performance, we used the image-level counts directly as count annotations. For the rest, we corrected CHM-derived tree counts using a linear regression $y = ax + b$ with 3-fold validation. Correction factors and final R^2 scores are reported in Supplementary Table 1.

Label distribution. For the Denmark subset, we picked images to have a roughly uniform distribution of canopy height due to a limited variation of height observed in our initial random image selection. For the France and Slovakia subsets, images were randomly picked without any filtering or visual inspection. For the Spain and Slovenia subsets, we purposely chose forest-dominated regions prior to random picking to ensure efficient coverage of forest landscapes. As such, the DRIFT dataset covers diverse label distributions representing many different real-world scenarios.

Supplementary Table 1: Image-level tree count annotation accuracy.

Dataset	# Images	Base R^2	3-fold R^2 with correction	Correction factors (b, a)
Denmark	13094	0.93 [26]	-	-
France	10298	0.83	0.81 ± 0.04	1.93, 0.77
Slovakia	3129	0.85	0.89 ± 0.03	1.79, 0.77
Slovenia	1903	0.65	0.77 ± 0.06	9.24, 0.56
Spain	1150	0.87	0.86 ± 0.04	10.5, 0.79



Supplementary Fig. 1: Examples in the DRIFT dataset. Labels on the right: canopy height in meters (1st row), tree count (2nd row), and tree cover fraction (3rd row).

8 VGG experiments

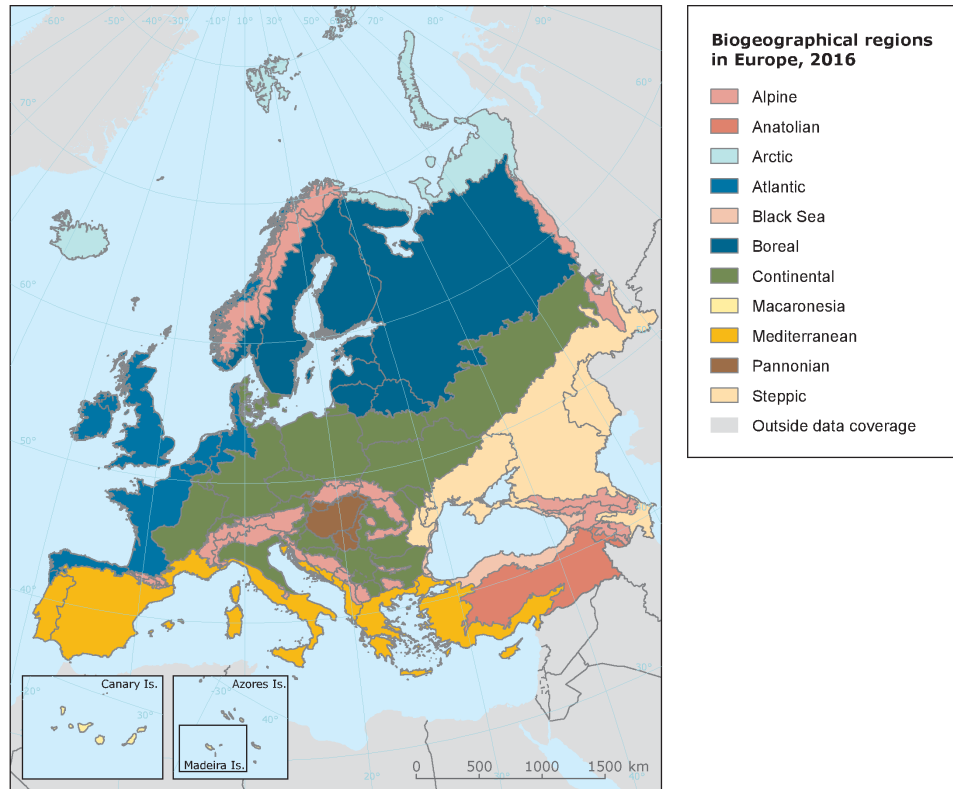
We repeat experiments with VGG [43] and report results in Supplementary Table 2. Our conclusions remain unchanged, with GOL+MDR and GOL+FT+MDR performing overall better than other methods except in setups with good off-the-shelf inductive performance. Compared to ViT, performance with VGG as a feature extractor is significantly lower everywhere, but the drop is smaller for transductive methods. For example, GOL+MDR performance drops by 0.03 in R^2 on average on counts, whereas FT performance drops by 0.27. It is also interesting to note that the drop in performance is the smallest across methods for the cover task, which corroborates our intuition that it is an easier task.

Supplementary Table 2: Comparison of methods on the DRIFT dataset (5-shot) with the VGG16 feature extractor. Average R^2 score across 3 random runs for FT and 10 random runs for the rest.

Source Target		Spain	Denmark Slovakia	Slovenia	Spain	France Slovakia	Slovenia	avg
Height	Regression	0.28	0.11	-0.01	0.53	-0.44	-0.13	0.06
	Regression cal.	0.23±0.09	0.51±0.05	0.41±0.04	0.55±0.05	0.34±0.08	0.35±0.02	0.40
	FT [25]	0.20±0.06	0.40±0.01	-0.02±0.09	0.55±0.00	-0.03±0.12	-0.31±0.02	0.13
	kNN	0.19±0.06	0.49±0.05	0.39±0.10	0.41±0.04	0.17±0.07	0.20±0.09	0.31
	GOL [24]	0.27±0.07	0.34±0.08	0.63±0.03	0.61±0.03	0.34±0.04	0.64±0.04	0.47
	GOL+MDR	0.58±0.03	0.43±0.04	0.62±0.06	0.58±0.04	0.41±0.03	0.66±0.02	0.55
	GOL+FT+MDR	0.59±0.01	0.50±0.01	0.64±0.03	0.54±0.03	0.44±0.02	0.64±0.03	0.56
Count	Regression	0.51	0.41	-0.05	0.49	0.43	-1.92	-0.02
	Regression cal.	0.45±0.06	0.40±0.08	0.08±0.06	0.50±0.05	0.51±0.04	0.41±0.06	0.39
	FT [25]	0.59±0.00	0.45±0.02	0.19±0.02	0.49±0.01	0.52±0.02	-0.80±0.07	0.24
	kNN	0.40±0.08	0.45±0.06	0.10±0.15	0.37±0.06	0.34±0.08	0.39±0.04	0.34
	GOL [24]	0.48±0.05	0.52±0.06	0.54±0.07	0.48±0.05	0.59±0.04	0.44±0.05	0.51
	GOL+MDR	0.48±0.04	0.55±0.04	0.58±0.04	0.52±0.04	0.60±0.03	0.45±0.07	0.53
	GOL+FT+MDR	0.54±0.05	0.53±0.01	0.43±0.07	0.51±0.01	0.59±0.01	0.34±0.06	0.49
Cover	Regression	0.44	0.69	0.66	0.78	0.61	0.54	0.62
	Regression cal.	0.61±0.02	0.79±0.01	0.63±0.04	0.80±0.02	0.74±0.01	0.62±0.06	0.70
	FT [25]	0.40±0.02	0.67±0.03	0.69±0.00	0.83±0.01	0.67±0.02	0.47±0.01	0.62
	kNN	0.45±0.05	0.66±0.04	0.56±0.13	0.69±0.03	0.63±0.04	0.67±0.06	0.61
	GOL [24]	0.48±0.08	0.68±0.03	0.59±0.09	0.75±0.03	0.73±0.03	0.62±0.08	0.64
	GOL+MDR	0.62±0.07	0.73±0.02	0.56±0.08	0.75±0.02	0.73±0.02	0.63±0.07	0.67
	GOL+FT+MDR	0.73±0.03	0.63±0.06	0.74±0.01	0.78±0.01	0.74±0.03	0.61±0.02	0.71

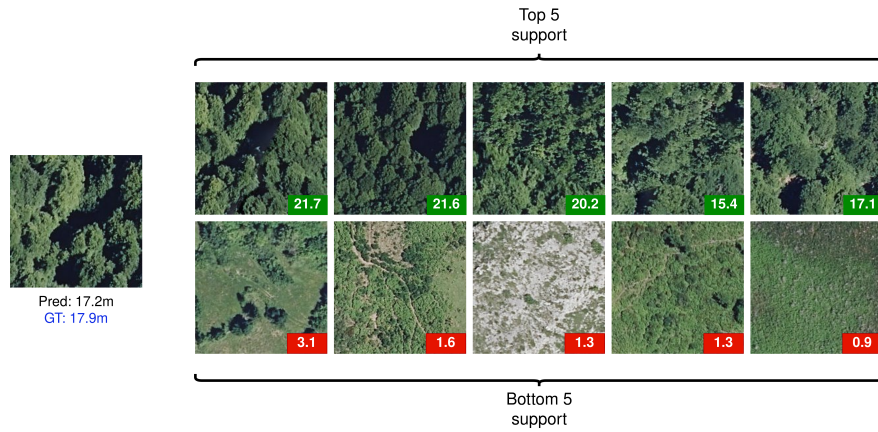
9 Biogeographical regions

Biomes influence the distribution of tree species, and at individual level their height, crown area, among other characteristics. The DRIFT dataset covers four major biomes: Mediterranean (Spain, France), Continental (France, Slovenia, Slovakia, Denmark), Alpine (Slovenia, Slovakia), Boreal (Denmark).

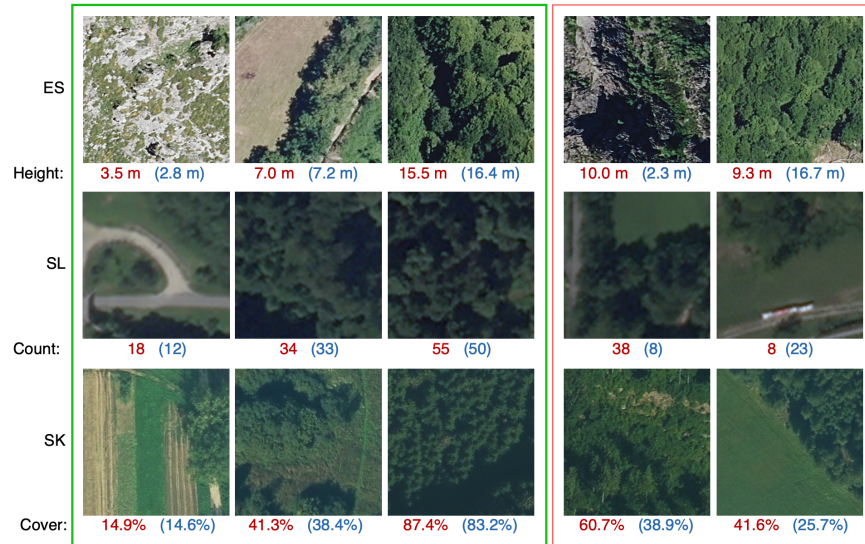


Supplementary Fig. 2: Biogeographical region distribution reflects the diversity of biomes in the DRIFT dataset. Image credits: European Environment Agency. <https://www.eea.europa.eu/data-and-maps/figures/biogeographical-regions-in-europe-2>

10 Qualitative results



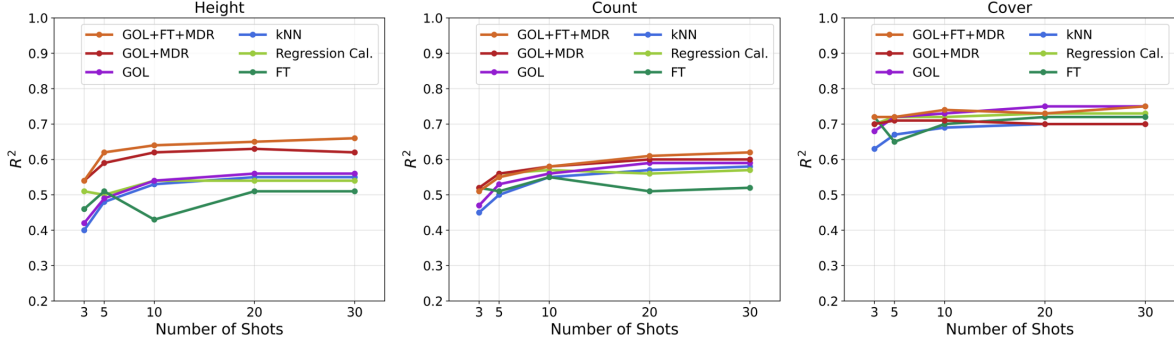
Supplementary Fig. 3: Visual results: five most similar and five least similar support examples for a query, after 5-shot GOL+MDR. Labels are shown in the bottom right corner.



Supplementary Fig. 4: Example predictions by 5-shot GOL+MDR: successful cases on the left (green box) and failure cases on the right (red box). Predictions are shown in red text and ground-truths are shown in blue text in brackets.

11 Effect of support set size

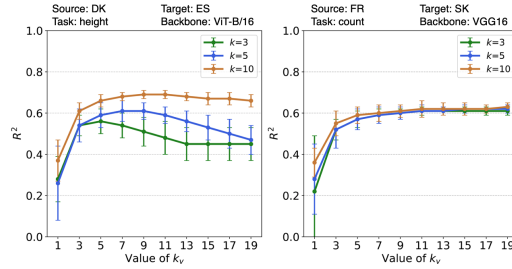
The performance on the height and count regression tasks increases until 20 shots (20 example per group, 100 in total), then saturates. For the cover task, performance saturates at 10-shots.



Supplementary Fig. 5: Sensitivity to the number of shots per group. Average R^2 score across two source domains and three target domains, with ViT-B/16 backbone.

12 MDR parameters

As the support set grows larger, the influence of the number of neighbors for kNN assignment diminishes.



Supplementary Fig. 6: Sensitivity to k_v in the weighted sum for combining relevant support samples. $k = N$ denotes the number of nearest neighbors for constructing the affinity matrix.