# Probing the lighting sensitivity of image encoders with repeat drone imagery: A case study of plant height estimation

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# **Abstract**

Image encoders provide a strong backbone for tasks such as retrieval, classification, and depth estimation, and recent releases tailored to remote sensing, such as DI-NOv3 with SAT pretraining [Siméoni et al., 2025], promise improved performance on ecologically important applications. It is uncertain whether such encoders yield robust features under variable illumination, where shadows and hue shifts can obscure relevant plant structure. To address this, we developed a drone imagery dataset with high-resolution RGB captures of the same site at three time points in a single day, paired with plant canopy height models. Using these data we identified the subspace of embeddings dominated by lighting variation and progressively projected embeddings away from lighting subspace components. Across both DI-NOv2 and DINOv3, canopy height prediction remained stable until more than 80% of the lighting variance was removed, after which performance degraded sharply, with a pronounced error spike when the full lighting subspace was eliminated. These results suggest that while much of the lighting variance is nuisance, the final fraction contains useful textural and chromatic cues. DINOv3-SAT consistently outperformed the general-purpose DINOv2, maintaining ~1 cm lower error until complete removal of the lighting subspace. We release the [BLINDED FOR RE-VIEW] dataset on Hugging Face under a Creative Commons 4.0 license to facilitate further exploration of lighting sensitivity in image encoders for remote sensing.

# 1 Introduction

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26 27 Foundational image encoders are widely used in computer vision for tasks such as classification, retrieval, depth estimation, and segmentation. Because they are trained on very large and diverse image datasets, they can be adapted to many different domains. Well-known examples include CLIP [Radford et al., 2021], DINOv2 [Oquab et al., 2023], and DINOv3 [Siméoni et al., 2025], all of which achieve strong results across a range of applications. Importantly, Siméoni Siméoni et al. [2025] introduced versions of DINOv3 specifically designed for aerial imagery, a form of earth observation data that differs substantially from the internet-based collections typically used for pretraining.

Remotely sensed earth observation data are predominantly of top-down perspective gathered by satellites, manned aircraft, and unmanned aerial vehicles (UAV's; drones). The most common form is optically sensed visible light imagery, though multi- and hyper-spectral sensors capturing non-visible wavelengths are also abundant and strongly correlate with physical and ecological phenomena [Rouse et al., 1973, Qi et al., 1994, Hall et al., 1995, McFeeters, 1996]. Some ecological targets for prediction with remotely sensed data include land cover [Justice et al., 1998], plant species composition [Feilhauer et al., 2017], chlorophyll content [Rouse et al., 1973], plant canopy height [Harris et al., 2021, Tolan et al., 2024], and others.

In aerial imagery, lighting conditions may vary dramatically which can impact performance on downstream tasks. In particular, cast shadows from clouds, terrain, vegetation, and built structures 37 can obscure critical features within imagery and harm biophysical indices, and identification of 38 shadows is a critical post-processing step in remote sensing [Hagolle et al., 2010, Zhu and Woodcock, 39 2012, Coleman et al., 2020, Alavipanah et al., 2022]. Relatedly, there is a rich literature base targeting 40 removal of shadows, including neural architectures, to address this challenge [Li et al., 2022, Liu 41 et al., 2022, Shao et al., 2025]. In some instances, shadows may enhance, e.g., tree detection, as 42 trees are likely to cast longer shadows than lower-lying vegetation [Hung et al., 2011]. However, 43 because shadows vary greatly with solar angle and atmospheric conditions, systems dependent on 44 these features are brittle. How sensitive aerial-specific foundation models like DINOv3 are to lighting 45 variation is largely unknown, despite illumination being one of the main factors that can alter the 46 quality of remote sensing products. 47

We contribute the [BLINDED FOR REVIEW] dataset to explore the sensitivity of image encoders to variable lighting conditions. In [BLINDED FOR REVIEW], high resolution aerial images of the same natural scenes were captured at three time points in a single day. The scenes were identical except for dramatic differences in illumination driven by change in solar position. With these data we studied the lighting sensitivity of DINO encoders [Oquab et al., 2023, Siméoni et al., 2025] by incrementally removing the variance attributed to lighting components of the feature space, and evaluated the effects on downstream error in plant canopy height prediction. We expected models to have rich representations for lighting and that a plant height decoder would exploit these features, as taller plants cast longer shadows. Furthermore, we expected performance would degrade as we removed increasing amounts of variance in the lighting subspace. Our approach provides a controlled framework to test the robustness of foundation models to nuisance illumination and their capacity to retain ecologically relevant signal.

# 2 Methods

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# 2.1 Site Description and Spatial Data Acquisition

The field site was located at [BLINDED FOR REVIEW]. Previously this area served as a working cattle ranch, but the land is now managed for wildlife conservation. Our survey site (**Fig. 1**) was 12 hectares in area and ranged in elevation from 972 to 1009 meters. Vegetation types are varied and include reclaimed agricultural fields, restored native grasslands, and conifer woodlands with interspersed dirt access roads.

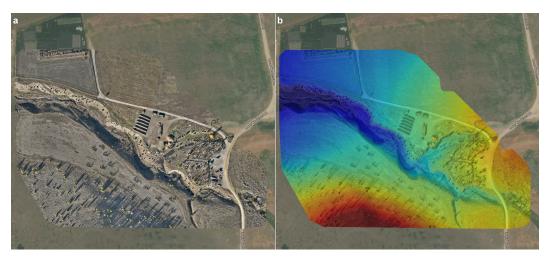


Figure 1: An orthoimage (a) of the 12-hectare survey site at [BLINDED FOR REVIEW] and accompanied elevation model (b).

We conducted drone surveys on November 9th, 2024, capturing the site with a DJI Mavic 3M with onboard real-time kinematic global navigation satellite systems. We gathered data at three time points: 10:00 am, 12:00 pm, and 3:00 pm, each survey lasting 25 minutes. We flew the drone at 50

meters above ground level, resulting in a ground sampling distance of 1.4 cm/pixel. We generated 2D orthomosaics and 3D point clouds with Drone Deploy (www.dronedeploy.com) using ground control to improve georeferencing, and this process resulted in three-dimensional spatial error of less than two centimeters.

To generate canopy height models for our study area, we combined drone-based point cloud data 74 with a bare-earth digital terrain model from the USGS 3D Elevation Project (3DEP; public domain; 75 Sugarbaker et al. [2014]). For each survey time point we classified drone point cloud data as ground 76 if the nearest neighbor in the 3DEP model differed by less than 1.4 centimeters along the z-axis 77 (Z-error of drone survey). Then for each time point we produced canopy height models following 78 normalization and rasterization methods described in [Roussel et al., 2020]. We then averaged canopy 79 height across the three time points to generate a single composite model which we used as the target 80 for prediction in subsequent analyses. 81

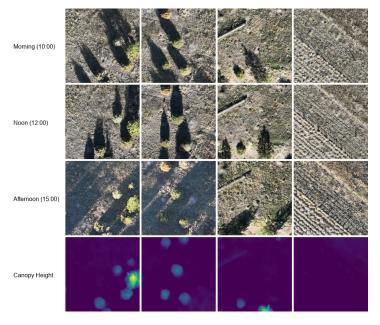


Figure 2: A sample of four tiles from the [BLINDED FOR REVIEW] dataset. Rows one through three contain images from the morning, noon, and afternoon captures, while the fourth row depicts the corresponding canopy height model targeted for prediction.

# 2.2 Dataset Preparation

We tiled the orthomosaics from each time point and canopy height model into squares that were 1024 pixels on a side (~14 meters; **Fig. 2**). We excluded any tile from further analysis if it contained transient objects, such as cars present in the morning and absent in the afternoon. This produced a total of 609 scenes, each with three RGB images corresponding to morning, noon, and afternoon scans and a corresponding canopy height model.

87 For each scene and time point, we pre-encoded RGB images using two vision transformer models: 88 DINOv2-Base (ViT-B/14; facebook/dinov2-base; Oquab et al. [2023]; Apache 2.0) and DINOv3-89 Large with SAT pretraining (ViT-L/16; facebook/dinov3-vitl16-pretrain-sat493m; Siméoni 90 et al. [2025]; custom license). Images were resized to  $224 \times 224$  pixels and normalized using 91 ImageNet statistics for DINOv2 [Russakovsky et al., 2015], and SAT-493M dataset statistics for 92 DINOv3 [Siméoni et al., 2025]. Each encoding produced a class token and a set of patch tokens: 93 class token dimensionality was 768 (DINOv2) and 1024 (DINOv3); patch tokens formed 2D arrays 94 of shape [256, 768] and [196, 1024], respectively. 95

We serve the [BLINDED FOR REVIEW] Dataset on Hugging Face with a Creative Commons 4.0 license in three configurations: 1) default – containing RGB images for three time points and canopy height model, 2) dinov2\_base, and 3) dinov3\_sat, each containing their respective patch

and class tokens. The dataset is split by tile index, with an 80/20, train/test regime. For further dataset details, refer to the [BLINDED FOR REVIEW] Hugging Face repository.

#### 2.3 Lighting Subspace Removal Experiment

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To test the sensitivity of encoders to illumination, we identified the variance associated with lighting 102 and progressively removed it from embeddings. We pooled and mean-centered patch tokens from all 103 three time points and then applied singular value decomposition to the resulting embedding matrix to 104 extract orthogonal components ordered by explained variance. The leading components captured the 105 dominant variation shared across time, which we interpret as being largely driven by lighting and 106 shadows. We defined this set of components as the lighting subspace. 107

Each patch token was projected away from the first k components of this subspace, yielding modified features that progressively excluded lighting-related variance (Fig. 3). These projected embeddings were then used to train a decoder to predict canopy height. This procedure allowed us to measure how prediction error changed as lighting variance was increasingly filtered from the representation. Because DINOv2 and DINOv3 differ in patch token dimensionality, we report the percentage of lighting-related variance removed rather than the raw number of components, for ease of interpretation.

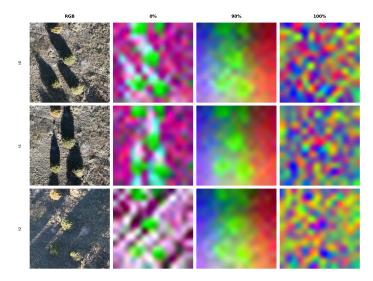


Figure 3: An example tile at three points with depictions of the DINOv3 feature space remaining after removal of k components representing 0, 90, and 100% of the variance attributed to lighting. The first three components after lighting subspace removal are mapped to RGB colorspace.

# 2.4 Decoder Architecture, Training Procedure, and Evaluation Regime

We developed a lightweight convolutional decoder to map projected token embeddings to canopy 116 height, following standard encoder-decoder designs [Ronneberger et al., 2015, Badrinarayanan et al., 2017] with GroupNorm [Wu and He, 2018] and GELU activations [Hendrycks and Gimpel, 2016]. We trained for 50 epochs with AdamW (learning rate 1e-3) and mean squared error loss.

We conducted five-fold cross-validation where folds were established by random tile indices and maintained across experiment configurations. We computed the best cross-validated epoch for each configuration and report performance as the cross-validated mean RMSE of canopy height (cm) and associated 95% confidence interval. In total there were 110 configurations: 2 Models × 11 lighting subspace conditions × 5 folds. This consumed an estimated 55 hours of compute across eight nodes, each with an Nvidia A6000 GPU, 32G RAM, and 8 CPU's.

#### 3 Results and Discussion

Across both DINO models, canopy height prediction remained stable even after removing large fractions of the lighting subspace (**Fig. 4**). Performance declined only beyond 80% variance removal, with a sharp error spike at 100%, suggesting that critical semantic information was eliminated alongside lighting effects. The satellite-specialized DINOv3-Large (SAT pretraining; [Siméoni et al., 2025]) consistently outperformed DINOv2 [Oquab et al., 2023], maintaining ~1 cm lower error until complete removal of the lighting subspace.

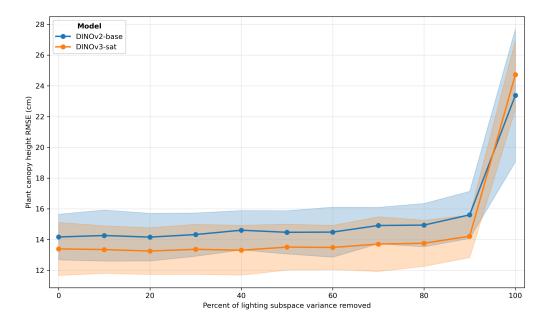


Figure 4: Performance of DINOv2-base and DINOv3-sat models on canopy height estimation from drone imagery under progressive removal of lighting subspace components. The x-axis shows the cumulative percentage of lighting-related variance removed (via SVD projection), and the y-axis shows canopy height prediction error (RMSE, cm).

We suspect that the final portion of the lighting subspace, while still explaining variance across time, contained ecologically relevant texture and hue information. Fine-scale shadow patterns cast by grass stems, broad leaves, or conifer needles likely carry distinct morphological signatures that aid discrimination among plant functional types. Similarly, because imagery was collected in autumn, senesced grasses presented muted hues that contrasted with evergreen vegetation; removing the full complement of lighting-related variance may have suppressed these subtle chromatic cues, thereby reducing the model's ability to distinguish evergreen plants from a chlorotic background.

Our analysis is limited to a single grassland—woodland site on a single calendar day, so results may differ in other contexts such as densely forested regions, open arid environments, or seasons with more uniform green foliage. Nevertheless, the [BLINDED FOR REVIEW] dataset demonstrates the value of rapidly repeated drone imagery for probing the behavior of image encoders. Our findings further indicate that both current and prior generations of encoders are robust to substantial variation in lighting, and that the DINO family in particular mitigates nuisance illumination effects that have previously challenged remote sensing analyses. These properties suggest strong potential for predicting other ecologically relevant traits beyond canopy height.

# 4 Data and Code Availability

To adhere to practices of double-blind peer review we serve an anonymized version of our dataset on Hugging Face. Please find code for lighting subspace removal experiments in the following directory of the repository.

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- Providing as much information as possible in supplemental material (appended to the paper) is recommended, but including URLs to data and code is permitted.

#### 6. Experimental setting/details

Question: Does the paper specify all the training and test details (e.g., data splits, hyper-parameters, how they were chosen, type of optimizer, etc.) necessary to understand the results?

Answer: [Yes]

Justification: We provide training details here 2.4.

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- The answer NA means that the paper does not include experiments.
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Question: Does the paper report error bars suitably and correctly defined or other appropriate information about the statistical significance of the experiments?

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Question: For each experiment, does the paper provide sufficient information on the computer resources (type of compute workers, memory, time of execution) needed to reproduce the experiments?

Answer: [Yes]

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Justification: We provide details of compute resources here 2.4

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