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ABSTRACT

Aerial imagery from drones and airplanes is increasingly used as reference data for satellite remote sensing. Linking an orthophoto to the satellite observations of the same time requires its acquisition date. In crowd-sourced aerial archives, this reported acquisition date can be incorrect or incomplete. Yet no method exists to verify or estimate it from the data. Here, we develop AerialStamp, a method that estimates the acquisition date of an aerial orthophoto, from a drone or an aircraft, as a calibrated probability distribution over the days of the flight year. The model combines DINOv2 embeddings of 10 cm patches of the orthophoto with the Sentinel-2 time series of the site. For every week of that series, spatial correlation features describe how well the orthophoto, averaged to 10 m, correlates across pixels with the Sentinel-2 image of that week. We used 6,984 publicly available orthophotos from 129 countries in the crowd-sourced database deadtrees.earth. Spatial block cross-validation yields a median absolute error of 18.5 days (mean 30.3 days), where for 7% of orthophotos the estimated and submitted dates differed by more than 90 days. Within the dataset of crowd-sourced aerial images, at least 1.3% of the acquisition dates were detected to be wrong. A further 10.3% fall on the 1st or 15th of a month, days that are submitted about 1.6 times as often as expected by chance and therefore likely serve as placeholders. The resulting framework is available as a Python package (github.com/cmosig/aerialstamp) and is being integrated into the platform deadtrees.earth.

1. Introduction

Aerial imagery from drones and airplanes is used across domains as reference for satellite-based remote sensing, for example in land use and land cover mapping and in environmental monitoring. For vegetation monitoring, a range of studies showed that features such as invasive species (Kattenborn et al., 2019), mortality (Schiefer et al., 2023; Mosig et al., 2026a), vegetation cover (Riihimäki et al., 2019), and burned areas (Fernández-Guisuraga et al., 2018) can be readily identified in drone images and serve as scalable reference for training and validating satellite-based models (Alvarez-Vanhard et al., 2021; Kattenborn et al., 2021).

The acquisition date of an orthophoto makes it possible to synchronize these reference observations with Earth observation satellite data (Mosig et al., 2026a; Kattenborn et al., 2019). Errors in the acquisition date would pair the orthophoto with non-corresponding satellite observations, limiting model training or validation. For applications such as phenological monitoring, date shifts of several weeks already exceed the required accuracy.

In crowd-sourced databases such as deadtrees.earth (Mosig et al., 2026b), OpenAerialMap (OpenAerialMap, 2026), or GeoNadir (GeoNadir, 2026), the date is entered by the contributor, and as with other volunteered geographic

information, its quality is heterogeneous and rarely verified (Goodchild, 2007; Senaratne et al., 2017). For example, in deadtrees.earth, the 1st and the 15th of the month are submitted about 1.6 times more often than other days of the month, and 1 January more than twice as often as expected by chance, which suggests that these are often placeholder days. Further, the order of day and month can be confused, as the established standard depends on the country (e.g. mm-dd-yyyy vs. dd-mm-yyyy). Verifying such dates by eye is hardly possible at scale, and missing dates cannot be checked at all. A method that estimates the acquisition date from the data would allow checking the plausibility of submitted dates and proposing dates where they are entirely missing. Such an approach would also allow recovering acquisition dates within large aerial mosaics, such as those of national aerial surveys, where flight lines often differ in acquisition date.

Estimating when an image was taken has so far been studied almost exclusively for ground-level photographs. Early work dated historical photographs (Palermo et al., 2012; Müller et al., 2017) and exploited the regular temporal variation of outdoor webcam scenes (Jacobs et al., 2007). More recent work learns joint representations of location and time from ground-level images and predicts the month and hour of capture as cyclical targets (Zhai et al., 2018; Salem et al., 2020; Shatwell et al., 2025), or checks whether claimed time metadata are consistent with image content and location (Kakar and Sudha, 2012; Padilha et al., 2022). For

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overhead imagery, seasonality has been used as a signal for self-supervised pre-training (Mañas et al., 2021), and drone and satellite observations of phenology have been compared across scales (Klosterman et al., 2018; Berra et al., 2019; Thapa et al., 2021). To our knowledge, however, no method estimates the acquisition day of year of georeferenced aerial imagery.

To fill this gap, we present AerialStamp, a method that estimates the day of the year on which an aerial orthophoto was acquired based on circular distributions, as is common in phenological studies (Morellato et al., 2010; Pabon-Moreno et al., 2020). It uses the orthophoto, its location and submitted year, and the weekly Sentinel-2 time series of the site, and returns a probability for every day of the year. Specifically, we aim to (i) establish acquisition-date estimation of crowd-sourced aerial orthophotos as a task, with a spatially blocked evaluation on a dataset of 6,984 orthophotos worldwide, (ii) quantify how much of the accuracy comes from Sentinel-2, by comparing a model with and without the Sentinel-2 time series, and from the spatial correlation features that compare the orthophoto with each week of that series, and (iii) demonstrate the utility of the method using the example of deadtrees.earth, by measuring how many of its submitted dates are potentially wrong or placeholders.

2. Data

2.1. Orthophotos

We used the 6,984 orthophotos of deadtrees.earth (Mosig et al., 2026b) that are publicly available under a CC BY license and have a Sentinel-2 series, that is, 6,689 drone and 295 airborne acquisitions with a median ground sampling distance of 3.3 cm (10th to 90th percentile 1.3–7.7 cm). They cover 129 countries on all continents except Antarctica (Fig. 1, Table 1). Most orthophotos lie in Europe (39%) and North America (20%), followed by South America (15%), Asia (14%), Africa (9%) and Oceania (2%), and 25% lie in the southern hemisphere. The flights date from 2015 to 2026, with a median of 2023 and 81% since 2020. For 5,180 orthophotos, the manual audit of deadtrees.earth (Mosig et al., 2026b) provides an *area of interest* (AOI), a multi-polygon of the part of the orthophoto without distortions; for the other 1,804, the whole orthophoto served as AOI.

2.2. Date labels

The acquisition date of each orthophoto is provided by the contributor at upload. We refer to it as the *submitted date* and to its year as the *submitted year*, and used both as provided. Of the 6,984 orthophotos, 6,936 have a *full date* (year, month and day) and 48 only a year and month; orthophotos with only a submitted year were not included.

The 1st and the 15th of the month are over-represented among the full dates, with 360 and 351 orthophotos against about 228 expected for any day of the month, as is 1 January with 51 against about 19. We assume that these days were

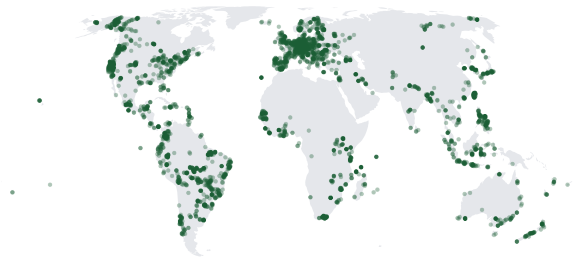


Figure 1: Locations of the 6,984 orthophotos, one translucent point each, in the Equal Earth projection (EPSG:8857).

Table 1

Orthophotos by continent and biome (6,984 in total; share in %). Biome separation is based on Olson et al. (2001) and consists of boreal and montane, dryland, temperate and (sub) tropical sites: 50% are temperate, 33% (sub) tropical, 11% drylands and 6% boreal and montane. Continents follow the 1:110m countries of Natural Earth (Natural Earth, 2026); remote islands are sites more than 200 km from any of these country polygons.

Continent	<i>n</i>	%	Biome	<i>n</i>	%
Europe	2,740	39	Temperate	3,493	50
North America	1,369	20	(Sub) Tropical	2,313	33
South America	1,014	15	Drylands	743	11
Asia	984	14	Boreal and Montane	433	6
Africa	622	9			
Oceania	174	2			
Remote islands	81	1			

often entered when only the month or the year was known and refer to them as *placeholder days*. The 711 full dates on placeholder days (10.3%) were excluded from training and evaluation. They comprise 51 dates on 1 January (*1 January placeholders*) and 660 dates on the 1st or 15th of a month other than 1 January (*1st/15th placeholders*).

The remaining 6,225 full dates are referred to as *clean dates* and form the *evaluation set*. They were used for both training and evaluation in a five-fold spatial block cross-validation (Section 2.4), in which each clean date is predicted by models trained on the other four folds. The 48 year-and-month labels were added to the training folds only, which gives 6,273 training labels in total.

2.3. Sentinel-2

For each orthophoto location, a Sentinel-2 (Drusch et al., 2012) Level-2A time series of 7-day mean composites of the 12 bands at 10 m resolution in the local Universal Transverse Mercator (UTM) zone was prepared with sentle, an open-source Python package for Sentinel-1 and -2 data cube generation, as in Mosig et al. (2026a). Clouds were masked with the CloudSEN12 cloud classifier (Aybar et al., 2022) and snow with the snow test of Fmask (Zhu and Woodcock, 2012), both as implemented in sentle. The series start in July 2015 and end when they were downloaded, between July 2025 and May 2026. All 12 bands enter the S2 model as

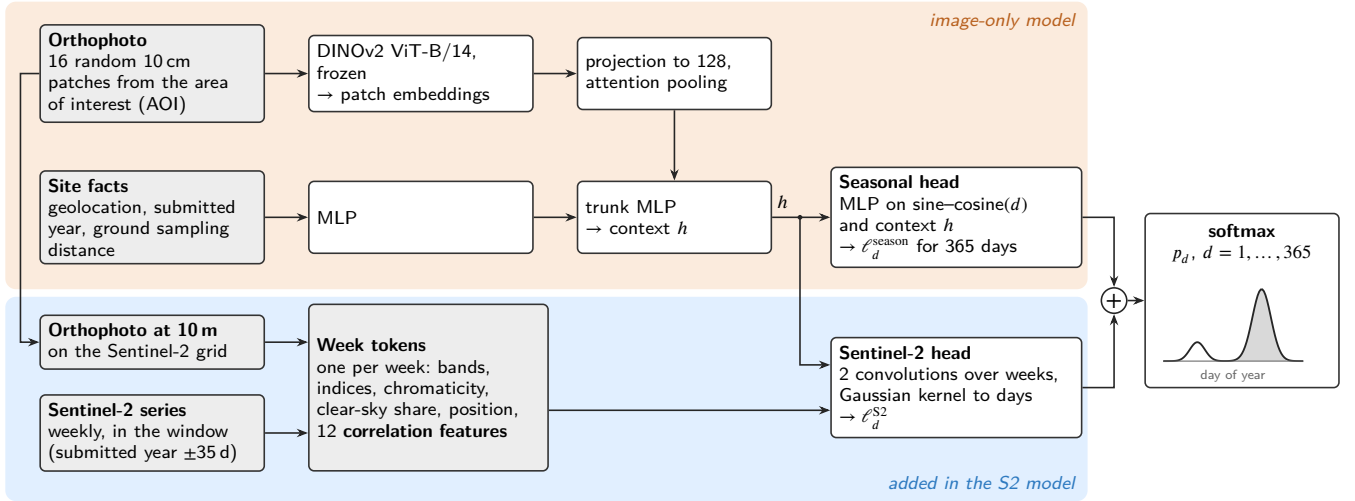


Figure 2: Overview of the two models. The image-only model consists of the components on the orange background and predicts the distribution from the seasonal head alone. The S2 model adds the components on the blue background and predicts the softmax of the sum of the seasonal and the Sentinel-2 scores (Eq. 1). In the S2 model, the orthophoto enters twice: as 16 random 10 cm patches embedded by DINOv2, and averaged to 10 m in the correlation features, which compare it with the Sentinel-2 image of each week (Table 2). Gray boxes: inputs; white boxes: network modules.

time series; the visible bands (B02, B03, B04) and the near-infrared band (B08) are additionally compared with the RGB orthophoto (Section 3.2).

2.4. Spatial blocking

To prevent spatial autocorrelation between training and test data from inflating the accuracy (Kattenborn et al., 2022; Nowosad et al., 2026), we split the data by spatial blocks. We assigned each orthophoto to a 50 km cell in the Equal Earth projection (EPSG:8857). Orthophotos of one campaign are often uploaded together with the same date, so we merged cells whenever two orthophotos within 500 km share the uploading account and flight date, or the authors listed in the metadata and flight date. The resulting 1,308 *spatial blocks* were assigned to five folds by group k -fold with the blocks as groups, stratified by biome (Roberts et al., 2017; Ploton et al., 2020).

3. Methods

AerialStamp consists of two models that estimate the acquisition date of an orthophoto as a probability distribution over the days of the submitted year, which we assume to be the flight year (Fig. 2):

1. The *image-only model* uses only the orthophoto and the *site facts* (geolocation, submitted year and ground sampling distance).
2. The *S2 model* (S2: Sentinel-2) is the same model with the weekly Sentinel-2 series of the site as additional input. For each week, *spatial correlation features* (in the following, correlation features) describe how well the orthophoto matches the Sentinel-2 image of that week.

The inputs are described in Section 3.2, the model in Section 3.3, and training and calibration in Sections 3.4 and 3.5.

3.1. Target

We divided the year into 365 day bins on a circle, so that 31 December is adjacent to 1 January; leap years lose one bin. The model returns a probability p_d for every day d . Although Sentinel-2 enters as weekly composites, the estimate has daily resolution: the seasonal head scores every day directly, and the Sentinel-2 head spreads its weekly scores to days (Section 3.3). A full date becomes a wrapped Gaussian target y ($\sigma = 3$ days) centered on the submitted day, and a year-and-month label a uniform target over that month. A distribution on the circle is required because many orthophotos visually fit several seasons, for example spring and autumn, or two wet seasons in the tropics.

3.2. Inputs

The S2 model receives three inputs (Fig. 2): 10 cm patches of the orthophoto, week tokens built from the Sentinel-2 series of the site, and *site facts*, i.e. the geolocation, the submitted year and the ground sampling distance. The image-only model receives the 10 cm patches and the site facts.

10 cm patches. We randomly drew 16 patches of 224×224 pixels at 10 cm resolution (22.4 m side) inside the AOI and embedded each with a frozen DINOv2 vision transformer with registers (ViT-B/14: base size, 14-pixel tokens; Oquab et al., 2024; Darcet et al., 2024). The class token and the mean patch token together form the *patch embedding* of 1,536 values. DINOv3 backbones (Siméoni et al., 2025) did not improve our results (Appendix A).

Week tokens. One token for each weekly Sentinel-2 composite in the *window* from 35 days before to 35 days after the submitted year, totaling up to 64 weeks. Each token holds the AOI mean reflectance of the 12 bands (square-root transformed, which spreads the low reflectance values typical of vegetation), the normalized difference vegetation

Table 2

Orthophoto-to-Sentinel-2 correlation features of a week, computed over the matched pixels. R, G, B: orthophoto bands averaged to 10 m; B02, B03, B04, B08: Sentinel-2 blue, green, red and near-infrared bands. Brightness, chromaticity (chrom.) and the indices are defined in Section 3.2.

Feature	Orthophoto	Sentinel-2
<i>Pearson correlation across matched pixels</i>		
red, green, blue	R, G, B	B04, B03, B02
brightness	brightness	brightness
green chromaticity	green chrom.	green chrom.
NGRDI	NGRDI	NGRDI
NGRDI vs. NDVI	NGRDI	NDVI
brightness vs. near infrared	brightness	B08
<i>Spearman correlation across matched pixels</i>		
brightness	brightness	brightness
<i>Other</i>		
green chromaticity difference	mean	mean
red chromaticity difference	mean	mean
matched share	matched / orthophoto-covered pixels	

index (NDVI; Rouse et al., 1974), the normalized difference moisture index (NDMI; Wilson and Sader, 2002), the normalized green–red difference index (NGRDI; Tucker, 1979), the green and red chromaticity (Gillespie et al., 1987), the clear-sky share (the share of clear AOI pixels), the position of the week in the year, and 12 orthophoto-to-Sentinel-2 correlation features (Table 2). NDVI, $(B08 - B04)/(B08 + B04)$, and NDMI, $(B08 - B11)/(B08 + B11)$, are commonly used indices of canopy greenness and water content. NGRDI and the chromaticities describe greenness and color in the visible bands alone and can therefore also be computed from the RGB orthophoto. With the *brightness* defined as the sum of the visible bands ($R + G + B$ for the orthophoto, $B02 + B03 + B04$ for Sentinel-2), the green chromaticity is the share of the green band in the brightness, e.g. $G/(R + G + B)$, the red chromaticity is defined analogously, and NGRDI is $(G - R)/(G + R)$ for the orthophoto and $(B03 - B04)/(B03 + B04)$ for Sentinel-2.

To compute the correlation features, we averaged the RGB orthophoto onto the 10 m Sentinel-2 grid and compared it with the Sentinel-2 image of the week over the *matched pixels*: those that the orthophoto covers to at least 80% and that are clear in Sentinel-2. Nine features are correlations across the matched pixels between one quantity of the orthophoto and one of Sentinel-2, for example the red channel and band B04 (Table 2): eight Pearson correlations and, for brightness, also the Spearman rank correlation. The other three are the differences in mean green and red chromaticity between Sentinel-2 and the orthophoto and the share of matched pixels. A correlation across pixels measures whether the two images share a spatial pattern, for example which fields are green and which are bare. The orthophoto values were used as stored, as 8-bit digital numbers without radiometric calibration. A correlation does not change when a quantity is linearly rescaled, and the chromaticities and NGRDI do not depend on the overall scale of the values, so orthophotos from uncalibrated consumer cameras can be compared with Sentinel-2 reflectance.

Site facts. The geolocation as latitude and longitude in a sine–cosine encoding, which maps a cyclic variable x with period P to $\sin(2\pi x/P)$ and $\cos(2\pi x/P)$ so that both ends of the cycle are close (Mac Aodha et al., 2019) (here $P = 360^\circ$); in addition, the latitude itself, the hemisphere, the submitted year and the ground sampling distance. The submitted year also selects the window of the week tokens. The position of the week in the week tokens is encoded in the same way ($P = \text{one year}$).

3.3. Model

The S2 model scores every day d of the year with two heads (Fig. 2); the image-only model uses only the first. The *seasonal head* returns a score ℓ_d^{season} for how well day d fits the appearance of the orthophoto at its location, and the *Sentinel-2 head* a score ℓ_d^{S2} for how well the orthophoto matches the Sentinel-2 images of the weeks around day d . The predicted distribution is the softmax of their sum,

$$p_d = \text{softmax}_d (\ell_d^{\text{season}} + \ell_d^{\text{S2}}). \quad (1)$$

Both heads receive a context vector h that summarizes the orthophoto and its site. The embeddings of the 10 cm patches are layer-normalized, projected to 128 dimensions and pooled by multi-head attention with one learned query; a trunk multilayer perceptron (MLP) combines the pooled embedding with an embedding of the site facts into h (256 dimensions). The seasonal head applies a two-layer MLP to the sum of linear projections of h and of a sine–cosine encoding of d (first four harmonics). The Sentinel-2 head adds a projection of h to each projected week token, applies two 1-D convolutions of width 5 weeks over the sequence of weeks, in which missing weeks are set to zero, and returns a score g_w per week w . A Gaussian kernel $k_{dw} = \exp(-(d - t_w)^2/2b^2)$ with a learned width b spreads the week scores to days,

$$\ell_d^{\text{S2}} = \frac{\sum_w k_{dw} g_w}{\sum_w k_{dw} + 0.1}, \quad (2)$$

where t_w is the position of week w in days from 1 January of the submitted year, so that the weeks of the ± 35 -day margins inform the first and last days of the year. The sums run over all weeks of the window, cloudy ones included, whose clear-sky share is part of their token. The constant 0.1 lets the term fade out where the series has no week near day d , for example after its end.

3.4. Training

To cope with potentially wrong submitted dates, we trained both models with a noise-robust negative log-likelihood of the target y as the loss,

$$\mathcal{L} = -\log \left(\frac{\epsilon}{365} + (1 - \epsilon) \sum_d p_d y_d \right), \quad \epsilon = 0.05, \quad (3)$$

which mixes the predicted distribution with a uniform distribution and thus caps the loss of a single wrong label at $-\log(\epsilon/365)$. We trained with AdamW (Loshchilov and

Hutter, 2019) (learning rate $5 \cdot 10^{-4}$, weight decay 0.05, one-cycle schedule (Smith and Topin, 2019), batch size 128) for 32 epochs without early stopping.

We used two data augmentations. In each step, 20% of the 16 patch embeddings were dropped. In addition, in 30% of the training samples the Sentinel-2 series was cut after a uniformly random day between 1 March of the submitted year and the end of the window (*window truncation*), because new uploads are recent and their Sentinel-2 series often ends inside the submitted year (Appendix B).

We trained five models with different random initializations and averaged their predicted distributions (ensemble); in cross-validation, this gives five models per fold.

The image-only model was trained with the same recipe and on the same orthophotos as the S2 model, but without the Sentinel-2 head.

3.5. Calibration

A predicted distribution is defined as calibrated when its prediction intervals contain the true date as often as their probability states, e.g. the 80% intervals for 80% of the orthophotos (Section 3.7). We calibrated the model ensemble with two parameters (Guo et al., 2017): a temperature T that flattens the distribution for $T > 1$, and a circular Gaussian smoothing of width s days,

$$p^{\text{cal}} \propto \text{smooth}_s(p^{1/T}). \quad (4)$$

For the orthophotos of each test fold, T and s were chosen on a grid to minimize the negative log-likelihood (NLL) of the submitted full dates, placeholder days included, in the out-of-fold predictions of the other four folds. The calibration thus never sees the test labels. For the S2 model, this gave $T = 2.0$ and $s = 0$ in every fold, and for the image-only model $T = 1.7$ and $s = 10$ days in four folds and $T = 2.0$ and $s = 0$ in one; values beyond the grid lowered the NLL by less than 0.001.

3.6. Naïve baselines

We additionally compare our models against three naïve baselines that predict the flight date from the typical flight dates of the region, from the phenology of the site, or from the most common flight date overall. The free parameters of Climatology and Phenology were chosen by maximum likelihood on the training folds. *Most common date* predicts for every orthophoto the most common flight day of the year in the training folds, the mode of a kernel density ($\sigma = 7$ days) of the training flight dates (3–5 July, depending on the fold), and uses that density as its distribution. *Climatology* is a kernel density ($\sigma = 7$ days) of the training flight dates, weighted by a Gaussian of the distance to the site, and mixed with the flight-date distribution of the same hemisphere. *Phenology* assumes that flights are more likely in leaf, $p_d \propto (c_d + a)^\gamma$, with c_d the *phenology curve* of the site, its long-term probability of being in the maximum greenness period on day d from satellite land surface phenology (Zhang et al., 2018), as in Mosig et al. (2026a).

3.7. Evaluation

All numbers are out-of-fold on the five spatially blocked folds. The *predicted date* is the circular median of p , which minimizes the expected absolute error. The *q prediction interval* is the smallest set of days that together hold the probability q (highest-density region; Hyndman, 1996). The error of an orthophoto is the circular distance between the predicted and the submitted date, the shorter way around the year (at most 182 days), so that 28 December and 3 January are 6 days apart. We report the mean absolute error (MAE) and the median error in days, and the share of orthophotos within ± 30 days of the submitted date. Because the spatial blocks were very uneven (the ten largest hold 29% of the training labels), we also report the block-weighted MAE (MAE bw), with each spatial block weighted equally; all other metrics weight every orthophoto equally.

3.8. Ablations

To quantify the contribution of the individual inputs, we retrained the S2 model with one component changed at a time: the image input to DINOv2, the patch embedding, and the content of the week tokens. Each variant was trained on the same folds as an ensemble of three models and was not calibrated (see Section 3.5). The variants are compared by the block-weighted MAE.

3.9. Validation with dense multitemporal drone data

To assess the consistency and the temporal biases of the models along dense time series, and to demonstrate them at well-known sites, we examined three sites flown repeatedly: the Leipzig floodplain forest (Germany), the ECOSENSE research station near Freiburg (Germany) and the 50 ha forest dynamics plot on Barro Colorado Island (Panama). We used the out-of-fold predictions; since the folds are grouped by spatial block, no flight was predicted by a model that saw its site. In addition to the MAE, we report Spearman's ρ between submitted and predicted day of year to reflect whether the model was successful in ordering the flights correctly, the share of correctly ordered pairs of flights of the same year by their time apart, and, for flights in July and August, whether the predicted distribution puts more probability into the submitted month than into the other. Since the flights of a series fall within one calendar year, we computed ρ on a linear time axis, after shifting each predicted date by a full year where this brought it within half a year of the submitted date. We did not use a circular correlation coefficient (Jammalamadaka and SenGupta, 2001), as it is measured around the mean direction of the dates, which is poorly defined for flights spread over the whole year.

3.10. Plausibility of submitted dates

For each full submitted date, we computed its *plausibility* π : the total probability of all days that the out-of-fold prediction of the S2 model finds at most as likely as the submitted day. Like a p -value, π is small when the submitted day is among the least likely days, and for a calibrated model and correct dates, a share α of the dates has $\pi < \alpha$ by

Table 3

Acquisition-date estimation on the 6,225 evaluation orthophotos (out-of-fold, spatial block cross-validation). All methods except Most common date also use the location of the site. MAE and median absolute error in days; bw: block-weighted; ± 30 : share of orthophotos dated within 30 days of the submitted dates.

Method	Input	MAE	MAE bw	median	± 30
<i>Baselines</i>					
Most common date	training flight dates	62.5	66.3	51.5	.32
Climatology	training flight dates	55.0	59.1	41.0	.39
Phenology	phenology curve	56.7	59.6	43.5	.36
<i>Learned models</i>					
Image-only model	10 cm patches, site facts	38.1	41.2	25.5	.56
S2 model	10 cm patches, site facts, week tokens	30.3	33.2	18.5	.66

Table 4

The methods of Table 3 by biome. MAE and median absolute error in days; n : evaluation orthophotos of the biome.

Method	Temperate $n = 3,148$		Boreal and Montane $n = 388$		(Sub) Tropical $n = 2,031$		Drylands $n = 656$	
	MAE	median	MAE	median	MAE	median	MAE	median
<i>Baselines</i>								
Most common date	45.8	36.5	37.9	23.5	86.6	81.6	82.3	76.6
Climatology	43.2	34.5	30.0	19.5	72.3	59.5	73.1	65.5
Phenology	41.9	34.5	37.5	23.7	74.8	62.5	83.1	78.1
<i>Learned models</i>								
Image-only model	28.6	20.5	23.6	13.5	50.8	36.5	52.5	36.5
S2 model	24.0	15.9	18.7	10.5	37.4	22.5	45.6	32.3

Table 5

Ablation of the S2 model: block-weighted MAE (days) on the evaluation set when one component is changed, and the difference Δ to the S2 model. Uncalibrated three-seed ensembles, hence 32.9 and 41.9 instead of 33.2 and 41.2 days as in Table 3; seed-to-seed standard deviation 0.1–0.5 days. Color statistics: 34 per-patch statistics (means, standard deviations and quantiles of color, brightness and the excess green index (Woebbecke et al., 1995), shares of color classes, and a hue histogram).

Variant	MAE bw	Δ
S2 model	32.9	
<i>Image input to DINOv2</i> (S2 model: 16 random 10 cm patches)		
none (orthophoto only in the correlation features)	39.4	+6.4
overview: AOI as one 224 × 224 image	40.5	+7.6
four 224 × 224 tiles at 1 m	37.5	+4.6
one 10 cm patch	36.0	+3.1
16 patches, mean instead of attention pooling	33.6	+0.7
<i>Patch embedding</i> (S2 model: DINOv2)		
34 color statistics instead of DINOv2	40.3	+7.4
DINOv2 and the 34 color statistics	33.8	+0.8
<i>Week tokens</i> (S2 model: bands, indices, correlation features)		
correlation features only	33.1	+0.2
bands and indices only	40.8	+7.9
none (image-only model)	41.9	+8.9

Table 6

Submitted full dates with a plausibility π below 0.05, 0.01 and 0.001 under the S2 model (out-of-fold); in brackets, the number expected by chance for a calibrated model if all dates were correct. Clean: dates not on placeholder days.

Full dates	n	$\pi < 0.05$	$\pi < 0.01$	$\pi < 0.001$
Clean dates	6,225	341 (311)	107 (62)	26 (6.2)
1st/15th placeholders	660	65 (33)	30 (6.6)	4 (0.7)
1 January placeholders	51	33 (2.6)	23 (0.5)	11 (0.05)
All	6,936	439 (347)	160 (69)	41 (6.9)

estimate is a lower bound, because a wrong date that falls into a plausible season cannot be detected, and because the calibration was fitted on submitted dates that include wrong ones, which widens the intervals. How well the month of a date fits is measured by the share of the predicted probability that falls into the submitted month. To test for confused day and month, we swapped them in the implausible dates ($\pi < 0.01$) where this gives a different valid date, and compared the number of swapped dates with $\pi \geq 0.05$ with the number expected for a random day of the year.

chance. Equivalently, a date with $\pi < \alpha$ lies outside the $1 - \alpha$ prediction interval. If n_α of N dates have $\pi < \alpha$, $n_\alpha - \alpha N$ therefore estimates the number of wrong dates. The

4. Results

4.1. Accuracy of the estimated acquisition dates

The S2 model estimated the acquisition date with a median error of 18.5 days and an MAE of 30.3 days (Table 3). 66% of the orthophotos were dated within ± 30 days and 23% within a week (Appendix C). The best baseline, Climatology, had a median error of 41.0 days, and Phenology 43.5 days. The image-only model, which uses the 10 cm patches and the site facts but no Sentinel-2 data, reached a median error of 25.5 days (MAE 38.1 days).

The prediction intervals were calibrated: the 50, 80 and 95% intervals contained the submitted date for 53, 80 and 95% of the orthophotos (Table C.1). Before calibration, the ensemble was over-confident: its 80% intervals were 55 days wide and contained the submitted date for only 61% of the orthophotos. After calibration, the 80% intervals were 96 days wide on average, against 157 and 197 days for Climatology and Phenology.

Performance depended on the biome (Table 4). Temperate and boreal and montane sites have sharp seasons and were dated with median errors of 15.9 and 10.5 days (MAE 24.0 and 18.7 days). (Sub) tropical sites (median 22.5, MAE 37.4 days) and drylands (32.3 and 45.6 days) were harder, and so was the southern hemisphere (MAE 39.5 against 27.4 days in the northern hemisphere), which has fewer training labels. In every biome, the S2 model reduced the MAE by 37 to 48% against the better of Climatology and Phenology, whose MAE ranged from 30.0 to 73.1 days across biomes. Coverage of the 80% intervals ranged from 0.73 (drylands) to 0.86 (boreal and montane).

The errors had a long tail, where for 7% of the orthophotos, the predicted and the submitted dates differed by more than 90 days, and these orthophotos accounted for 30% of the summed absolute error. The tail occurred in every biome (3% of the temperate and 14% of the dryland orthophotos) but was concentrated at (sub) tropical and dryland sites.

The ablations (see Table 5) showed that without the correlation features, the Sentinel-2 bands and indices of the window improved the block-weighted error by 1.0 days over the image-only model (40.8 against 41.9 days), whereas the correlation features alone gave almost the full gain (33.1 against 32.9 days). The 10 cm patches reduced the error from 39.4 days without an image input to 32.9 days. An overview image of the whole AOI (40.5 days) was no better than no image input, and four 1 m tiles (37.5 days) gave less than a third of the gain of the 10 cm patches; the S2 model without an image input still sees the orthophoto through the correlation features. One patch versus 16 increased the error by 3.1 days, mean instead of attention pooling by 0.7 days. The 34 simple color statistics were weaker than the DINOv2 embeddings (40.3 days) and also did not improve them (+0.8 days).

4.2. Plausibility π of the submitted dates

Of the 6,984 orthophotos, 6,936 have a full submitted date. Of these, 160 had a plausibility $\pi < 0.01$ (Section 3.10), where 69 are expected by chance, and 41 had

$\pi < 0.001$, where 7 are expected (Table 6). At least 91 dates (1.3%) are therefore wrong, and about 34 of the 41 dates with $\pi < 0.001$ are likely genuine errors. For the 711 dates on placeholder days (10.3%) that were excluded from the experiments (see Section 2.2), the results differed depending on the date. For the 1st/15th placeholders, the month was almost as plausible as for clean dates: 28% of the probability fell into the submitted month, against 30% for clean dates. Still, these dates had $\pi < 0.01$ more than four times as often as expected by chance. The 1 January placeholders were mostly wrong altogether: 75% had $\pi < 0.2$, against 20% expected, their predicted date was off by 120 days on average, and only 6% of the probability fell into January. Confused day and month explained few of the implausible dates: of the 160 dates with $\pi < 0.01$, 58 give a different valid date when day and month are swapped, and the swapped date was plausible ($\pi \geq 0.05$) for 30 of them, against 26 expected for a random day of the year.

Fig. 3 shows four examples. In the two cases with an implausible submitted date (Fig. 3b and 3c), the S2 model places the flight five and eight months after the submitted date, in a season in which the Sentinel-2 composite resembles the orthophoto visually more closely. In Fig. 3d, the distribution has two modes of similar size and the submitted date lies in one of them, so it is plausible ($\pi = 0.86$) although it lies 128 days from the predicted date, which falls next to the other mode.

4.3. Validation with dense multitemporal drone data

At the Leipzig floodplain forest (Germany), flown 43 times at near-weekly intervals from February to December 2025, the predicted dates followed the submitted ones with Spearman's $\rho = 0.99$ and an MAE of 13.3 days for the S2 model and 17.8 days for the image-only model (Fig. 4a). With the S2 model, flights 7–14 days apart were ordered correctly in 76% of the pairs, 14–30 days apart in 91% and 30–60 days apart in 97%, and six of the seven July and August flights were assigned to the right month. Since the image-only model alone reached $\rho = 0.99$, within a site the signal lies in the orthophoto itself. The S2 model pulled flights towards midsummer: flights from late May to mid June were predicted two to six weeks late, and those in the second half of September four to six weeks early. For the nine flights from November to February, both models were uncertain: the range between the 10th and 90th percentiles of the distribution spanned 124 days on average for the S2 model and 131 days for the image-only model.

At the ECOSENSE research station (Werner et al., 2024) near Freiburg (Germany), the S2 model dated the 27 flights of 2024–2026 with an MAE of 15.4 days, against 21.6 days for the image-only model (Fig. 4b): 16 flights in 2024 with 14.2 days ($\rho = 0.99$) and 10 flights in 2025 with 18.5 days ($\rho = 0.93$), against 19.9 and 21.3 days for the image-only model.

The 50 ha forest dynamics plot on Barro Colorado Island (Panama) is a semi-deciduous tropical forest, in which many

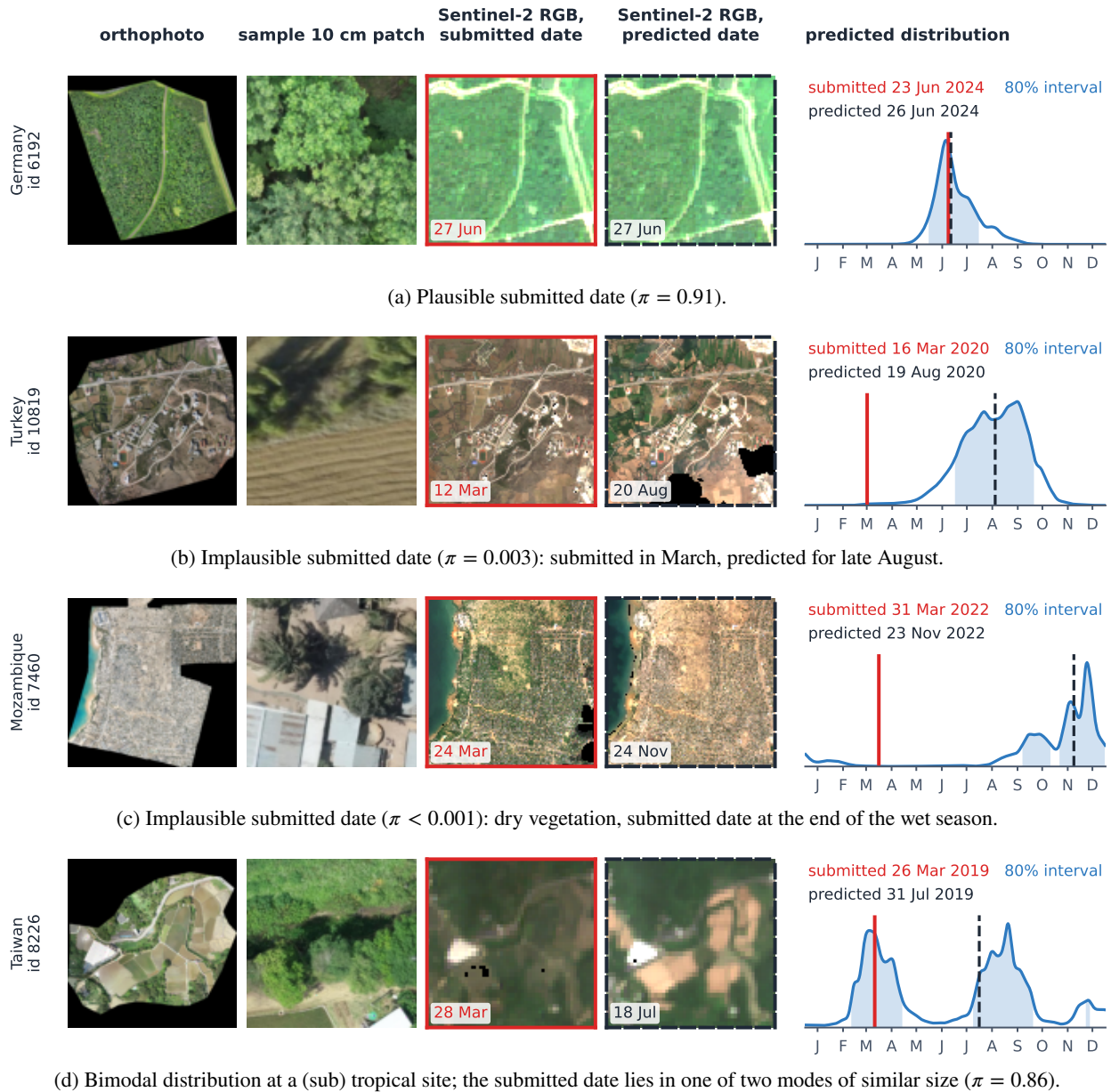


Figure 3: Four evaluation orthophotos with out-of-fold predictions of the S2 model and the plausibility π of the submitted date (Section 3.10). Columns from left to right: the orthophoto over its AOI, a sample 10 cm patch, the Sentinel-2 RGB composite (bands B04, B03, B02) of the weekly composite nearest the submitted date (red frame) and nearest the predicted date (black dashed frame), each with at least 90% clear AOI pixels and labeled with its date, and the predicted distribution over the submitted year. In the distribution, the red line marks the submitted date, the dashed line the predicted date, and the shaded area the 80% prediction interval. Dataset identifiers are accessible at deadtrees.earth/dataset/<ID>.

trees lose some or all of their leaves in the dry season from mid-December to mid-April (Park et al., 2019). It was flown about monthly from 2018 to 2023 and weekly in the 2023 dry season (90 flights; Vásquez et al., 2023) and was dated less accurately than the two temperate sites. The S2 model dated these flights with an MAE of 29.1 days ($\rho = 0.97$ over all years), and the image-only model with 69.9 days (Fig. 4c). With the image-only model, flights from January to March, the dry season, were dated two to five months off on average (MAE 64–168 days), and all 20 were placed in September to

December. With the S2 model, the errors dropped to 53 days in January, 33 days in February and 7 days in March, and six of seven March flights fell into March, whereas flights from May to August were predicted three to six weeks late. Among the weekly flights of 2023, the S2 model dated flights with an MAE of 18.7 days and ordered pairs 7–14 days apart correctly in 84% of cases, against 88.5 days and 53% for the image-only model.

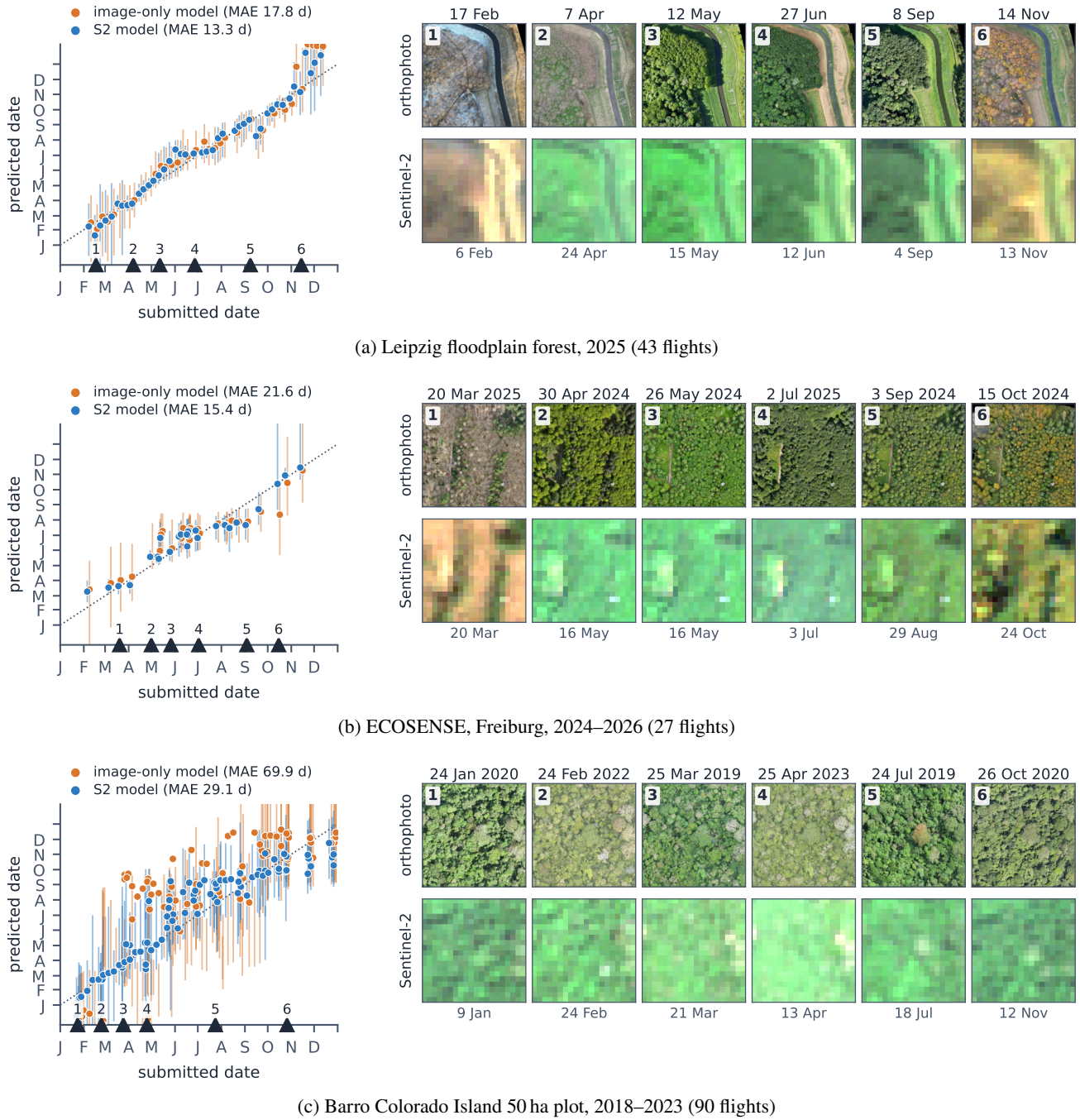


Figure 4: Three sites with dense multitemporal drone data. Left: predicted against submitted date (out-of-fold; blue: S2 model, orange: image-only model, drawn 3 days to the right of the S2 model; MAE over all flights of the site in brackets). Points show the predicted date, lines the range between the 10th and 90th percentiles of the predicted distribution; predictions are unwrapped to within half a year of the submitted date, so the axis extends beyond the calendar year. The dotted diagonal marks a perfect prediction. Triangles on the x-axis mark the submitted dates of the six numbered flights on the right. Right: these flights over the same 200×200 m cut-out (20×20 Sentinel-2 pixels): the orthophoto with its submitted date above, and below the Sentinel-2 RGB composite (B04, B03, B02) nearest the submitted date with at least 95% clear pixels, labeled with its date.

5. Discussion

5.1. Relevance of Sentinel-2 time series

Most of the improvement from Sentinel-2 came from the correlation features, and little from the bands and indices of the Sentinel-2 series itself (Table 5). The Sentinel-2 series of a site describes its seasons, but not which of them the orthophoto shows. The correlation features provide this information: the spatial arrangement of green and bare fields, of mown meadows, harvested crops or flooded areas changes from week to week, and the orthophoto matches only the weeks that share its arrangement. Because a correlation depends only on which pixels are brighter or greener than others, the features also work with the uncalibrated colors of consumer drone cameras (Section 3.2). The S2 model combines the correlation features of all weeks with the 10 cm patches, which show the seasonal state of the vegetation in detail. We hypothesize that the 10 cm patches carry phenological detail of individual crowns, such as flowering, leaf color and leaf-off branches, that is averaged out in coarser views.

The value of Sentinel-2 differed between biomes (Table 4). At temperate sites, the image-only model dated the evaluation set with a median error of 20.5 days (MAE 28.6 days), and Sentinel-2 reduced it to 15.9 days (MAE 24.0 days). At (sub) tropical sites, the median error dropped from 36.5 to 22.5 days (MAE 50.8 to 37.4 days). The dense time series show the same pattern: in the Leipzig floodplain forest, the image-only model ordered the flights of a year almost perfectly (MAE 17.8 against 13.3 days with Sentinel-2), whereas on Barro Colorado Island it dated dry-season flights two to five months off (MAE 69.9 against 29.1 days; Section 4.3). Temperate deciduous forests follow a leaf cycle that is visible in the orthophoto itself. In tropical forests, leaf exchange is often asynchronous among species and the canopy changes little between seasons (Park et al., 2019; Albert et al., 2019). Sentinel-2 is therefore most important for dating orthophotos in the tropics.

5.2. Limitations

Both models date the day within a submitted year and rely on that year: in the S2 model, a wrong year pairs the orthophoto with the wrong Sentinel-2 series and degrades the estimate to about the level of the image-only model (Appendix D). The year is partly recoverable from the data. In an exploratory analysis that is not part of the model, a small network ranked the ten candidate years 2016–2025 by the correlation features of each year and picked the submitted year for 50% of 6,335 orthophotos (73% within ± 1 year), against 19% for the most common year; the other orthophotos were flown in 2026 or have fewer than two candidate years. Estimating year and day jointly would remove the dependence on the submitted year.

The estimated numbers of wrong dates are lower bounds. A wrong date in a plausible season, a wrong day within the right season, or a date that matches the second mode of a bimodal distribution cannot be detected. Evergreen tropical forests, urban areas with little vegetation and dryland stands

that remain unchanged through a long dry season are the typical cases where the distribution stays broad or bimodal (Fig. 3d). The manual check marked only five of the dates used here as invalid, all of them on 1 January, too few to measure how well the S2 model detects known errors. Moreover, the 1st and 15th of the month are genuine flight days for some orthophotos, such as the eight flights on these days in the dense time series (Section 4.3), so excluding them from training discards correct labels.

5.3. Further applications

Linking drone or aerial imagery with satellite data is a growing field (Alvarez-Vanhard et al., 2021; Kattenborn et al., 2021), and all of its applications depend on the acquisition date, which links the image to the satellite observations of the same time. AerialStamp checks this link and supplies a date where none is recorded. Because it returns a probability for every day, the date uncertainty can be carried into the validation of satellite products, which removes one source of uncertainty that is otherwise unknown, in particular for crowd-sourced reference data.

Aerial surveys of large areas are often mosaics of flights in different months. Applied to tiles of such a mosaic, AerialStamp could estimate the flight date of each region and thus reconstruct the acquisition dates within the survey. Since the season can be read from an orthophoto with an error of a few weeks, the relation could also be used in reverse. Generative models of remote sensing imagery are conditioned on metadata such as location and time (Khanna et al., 2023); a date model can test whether a generated or augmented image matches its target season, or guide a seasonal augmentation of training data. We have not tested these applications.

6. Conclusion

We introduce AerialStamp, a method to estimate the acquisition date of crowd-sourced aerial orthophotos as a calibrated distribution over the days of the flight year, from the orthophoto and the Sentinel-2 time series of its site. In spatial block cross-validation on 6,225 publicly available orthophotos, the S2 model dated orthophotos with a median error of 18.5 days and calibrated prediction intervals. We show that most of the improvement from Sentinel-2 comes from simple correlation features, and that the 10 cm patches add to it. Sentinel-2 time series reduced the median error by 5 days at temperate and by 14 days at (sub) tropical sites. In deadtrees.earth, at least 1.3% of the submitted dates were detected to be wrong, and a further 10.3% fell on likely placeholder days. AerialStamp is being integrated into deadtrees.earth to check every upload and propose dates for review where the submitted date is missing or contradicts the data, and the AerialStamp package makes both models available to any user.

Code and data availability

AerialStamp, a Python package that dates a drone orthophoto with the S2 model or the image-only model and downloads the Sentinel-2 series with sentle (<https://github.com/cmogsig/sentle>), is available at <https://github.com/cmogsig/aerialstamp>. The data of this study (the model inputs of all 6,984 orthophotos, the spatial folds and the out-of-fold predictions of both models), the evaluation protocol and the code to train and evaluate the models are available as a benchmark at <https://github.com/cmogsig/aerialstamp-benchmark>. Orthophotos and metadata are available through deadtrees.earth (Mosig et al., 2026b), into which the model is being integrated.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Declaration of generative AI and AI-assisted technologies in the manuscript preparation process

During the preparation of this work the authors used Claude (Anthropic) for data analysis code, drafting and language editing. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

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A. DINOv3 vs. DINOv2

Table A.1 compares the DINOv2 embeddings of the 10 cm patches with three DINOv3 backbones (Siméoni et al., 2025): ViT-B/16 (base size, 16-pixel tokens) and ViT-L/16 (large size) trained on web images (LVD-1689M), and ViT-L/16 trained on satellite imagery (SAT-493M). The patches,

the embedding procedure (class token and mean patch token at 224 px) and the training setup were identical. All DINOv3 backbones gave a higher error than DINOv2, by 1.7 to 2.7 days for the S2 model and by 2.3 to 3.5 days for the image-only model; in all six comparisons, the 95% interval of the difference excluded zero.

Table A.1

Block-weighted MAE (days) on the evaluation set with different patch embeddings (calibrated five-seed ensembles). In brackets, the difference to DINOv2 with a 95% bootstrap interval over spatial blocks.

Backbone	S2 model	Image-only model
DINOv2 ViT-B/14	33.2	41.2
DINOv3 ViT-B/16	34.8 (+1.7; +0.5, +2.8)	43.5 (+2.3; +0.9, +3.7)
DINOv3 ViT-L/16	35.8 (+2.7; +1.3, +4.0)	44.7 (+3.5; +1.9, +5.1)
DINOv3 ViT-L/16 SAT	35.0 (+1.8; +0.5, +3.3)	43.6 (+2.4; +0.7, +4.1)

B. Forward in time and window truncation

To test the S2 model forward in time, we trained it on flights up to 2024 and evaluated it on the 1,550 orthophotos flown in 2025–2026. Without window truncation, the S2 model was much less accurate at sites whose Sentinel-2 series ended inside the submitted year. Where the series ended between July and October of the submitted year, its error was 47.3 days, against 35.8 days for the same sites in spatial cross-validation, where the training folds contain other 2025–2026 flights whose series also end inside the submitted year. Window truncation during training reduced the error at these sites to 37.5 days, the overall forward-in-time error from 47.1 to 38.9 days and the standard deviation of the forward error across seeds from 2.8 to 0.6 days, and it also reduced the error in spatial cross-validation from 34.1 to 33.1 days (Table B.1). Removing the year from the site facts made no consistent difference.

Table B.1

Block-weighted MAE of the S2 model in spatial cross-validation (all 6,225 evaluation orthophotos) and forward in time (trained on flights up to 2024, tested on the 1,550 orthophotos of 2025–2026), and the standard deviation of the forward MAE across three seeds (calibrated three-seed ensembles). Truncation: window truncation; the recipe with it is the S2 model. Errors in days.

Training recipe	MAE bw		
	spatial	forward	seed s.d.
Without truncation	34.1	47.1	2.8
With truncation (S2 model)	33.1	38.9	0.6
With truncation, no year input	32.8	37.9	1.1

C. Calibration and further accuracy metrics

Table C.1 complements Table 3 with the shares of orthophotos dated within 7 and 15 days and with the metrics of the predicted distribution (Section 3.7).

Table C.1

Further metrics for the methods of Table 3. $\pm 7/15$: share of orthophotos dated within that many days; coverage: share whose submitted date lies inside the 50/80/95% prediction interval; width: mean width of the 80% interval in days; NLL: negative log-likelihood of the submitted day. The baselines are fitted by maximum likelihood and not calibrated further.

Method	± 7	± 15	coverage	width	NLL
Most common date	.10	.18	.51/.80/.94	203	5.71
Climatology	.10	.21	.44/.74/.91	157	5.60
Phenology	.08	.19	.49/.81/.95	197	5.65
Image-only model	.16	.33	.50/.82/.96	123	5.14
S2 model	.23	.44	.53/.80/.95	96	4.89

D. Shifted year

To test how much the S2 model relies on the submitted year, we gave it a shifted year, i.e. the week tokens and the year in the site facts of the previous or the next year, for the 5,180 evaluation orthophotos with Sentinel-2 data in all three years. The error increased by 8 to 9 days, to about the level of the image-only model (Table D.1).

Table D.1

Error of the S2 model with the submitted and with a shifted year (week tokens and the year in the site facts of the previous or next year; $n = 5,180$ orthophotos with Sentinel-2 data in all three years; uncalibrated five-seed ensemble, hence the low coverage). Cov. 80%: coverage of the 80% prediction interval. Errors in days.

Year	MAE	MAE bw	cov. 80%
Submitted year (S2 model)	29.7	32.1	.62
Submitted year -1	37.4	40.8	.51
Submitted year +1	38.2	41.7	.50

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